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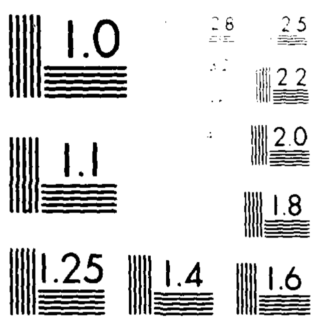

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INDIVIDUAL DIFFERENCES AND TIME-SHARING ABILITY: A CRITICAL REVIEW AND ANALYSIS

Phillip L. Ackerman, Walter Schneider, and Christopher D. Wickens

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Statistical methods employed to test individual differences in dual-task performance and the existence of a general time-sharing ability are reviewed and extensively critiqued. Specifically, both the types of data being collected and the types of procedures used in data analysis have been inadequate to the critical evaluation of a hypothetical "time-sharing" ability. Serious problems resulting from unsophisticated use of correlational and factor analytic procedures in methodology and analysis are discussed.

20. The application of such procedures to simulated data from a model with a hypothetical time-sharing factor accounting for 25 percent of the variance of scores in dual-tasks resulted in inappropriate rejection of the time-sharing factor. A number of recent psychometric findings and techniques, especially in the area of exploratory and confirmatory uses of factor analysis, are shown to have ramifications for research and analysis in this area. Data analytic techniques are presented which provide for convergent validational procedures appropriate to investigation of the time-sharing ability issue. In addition, the crucial nature of task selection,.scoring methods, and considerations of practice and reliability issues are discussed. Based on a reanalysis of available data, the "time-sharing" or "A" factor is not rejected. However, the lack of critical evidence presently available is demonstrated to prohibit the confirmation of such a factor. Simulation and incorporation of theory in planning models and crucial tests of the hypothetical "time-sharing" ability are discussed for use in further research.

Individual Differences and Time-sharing Ability

A Critical Review and Analysis

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Abstract

Statistical methods employed to test individual differences in dual-task performance and the existence of a general time-sharing ability are reviewed and extensively critiqued. Specifically, both the types of data being collected and the types of procedures used in data analysis have been inadequate to the critical evaluation of a hypothetical "time-sharing" ability. Serious problems resulting from unsophisticated use of correlational and factor analytic procedures in methodology and analysis are discussed. The application of such procedures to simulated data from a model with a hypothetical time-sharing factor accounting for 25 percent of the variance of scores in dual-tasks resulted in inappropriate rejection of the time-sharing factor. A number of recent psychometric findings and techniques, especially in the area of exploratory and confirmatory uses of factor analysis, are shown to have ramifications for research and analysis in this area. Data analytic techniques are presented which provide for convergent validational procedures appropriate to investigation of the time-sharing ability issue. In addition, the crucial nature of task selection, scoring methods, and considerations of practice and reliability issues are discussed. Based on a reanalysis of available data, the "time-sharing" or "A" factor is not rejected. However, the lack of critical evidence presently available is demonstrated to prohibit the confirmation of such a factor. Simulation and incorporation of theory in planning models and crucial tests of the hypothetical "time-sharing" ability are discussed for use in further research.

Individual Differences and Time-sharing Ability
A Critical Review and Analysis

The dual-task procedure has been a common paradigm in use by experimental psychologists for many years. This procedure has often been implemented in studies which have been concerned with determination of cognitive capacities, derivation of difficulty measures, modeling the structure of resources (see Navon & Gopher, 1979; Wickens, 1980; Kahneman, 1973; Welford, 1978). The present Zeitgeist in the human factors and learning areas has provided impetus for the consideration of individual differences within traditionally nomothetic investigations (see Gagne, 1967). By understanding between-individual sources of variance and relevant interactions, various types of experimental effects may be clearly observed and evaluated.

To allow fine-grain evaluation of human performance in dual-task and other complex task situations, an understanding of how subjects differ has been a crucial issue. Recent literature has focused on the question of whether time-sharing performance levels are the result of some task-specific skills or a pervasive ability of some subjects to perform complex behaviors. Information in this area will likely be important for selection and training of persons in any given complex task situation.

Of the handful of experiments that have focused on the attempt to demonstrate or refute the existence of such a "time-sharing" (T/S) ability, most have depended on interpretations from correlational data, especially with the aid of factor analytic techniques (see Hawkins, Rodriguez, & Reicher, 1979; Jennings & Chiles, 1977; Sverko, 1977; Wickens, Mountford, & Schreiner, 1979, 1981). However, there are several problems with these studies. These problems are introduced here and will be elaborated fully below. Some of these studies have made inappropriate use of data analytic techniques, considering the fact that theoretical specifications are necessary for proper use of factor analytic techniques. In fact, one of the basic tenets of this discussion is that factor analysis is not an atheoretical inferential technique. As such, application of the methods of factor analysis without consideration of requirements, assumptions, and practical rules of thumb found in the psychometric literature, often precludes the scientific discussion of data analytic conclusions. Given a set of conservative a priori assumptions about the nature of the hypothetical T/S ability (which will be described below), such forms of analysis are shown to be without any power for evaluating the presence of such an ability. Finally, serious flaws in initial experimental designs have further obscured the objective evaluation of the existence of the T/S ability.

In the discussion that follows, the following methodological and data analytic topics will be presented: 1) Appropriate models for the hypothetical T/S ability and heuristic methods for determining its existence. 2) Evaluation of technical aspects required to employ factor analysis to identify a general T/S ability. This includes consideration of a number of topics such as a) Choice of number of factors, b) Choice of variables and subjects, c) Factor rotation, d) Orthogonal and oblique factor structures, and e) Use of exploratory vs. confirmatory techniques.

3) Methods for the evaluation of subjects' relative performance levels in single and dual-task combinations. Also, even though the topic of practice has been given attention by other authors (see especially Damos & Smist, 1980; Jones, 1972), some discussion of the ramifications of practice on subsequent data analysis will be discussed.

Based on consideration of this broad range of topics, some demonstration of data analytic results with simulation will be presented. However, the major emphasis of the discussion will be the consideration of articles that have previously addressed the issue of individual differences in T/S abilities. Finally, conclusions from this review will be presented in which crucial tests for the T/S construct will be proposed.

Methodology and Data Analysis

Nature of the "Time-Sharing" Ability. When considering the existence of some hypothetical construct, researchers must be able to state (within a reasonably specific classification scheme) what the nature of the construct will be. The current literature suffers from two problems with respect to the construct of a T/S ability. The major problem has been associated with overly simplistic views of an ability to perform any two or more tasks simultaneously; little or no consideration has been provided to other factors, such as practice, single task performance level, performance variability, etc. The second problem is that the nature of a hypothetical T/S ability, per se, is partly determined by one's adherence to a specific theoretical perspective. These considerations would involve determining the behavioral extensions from the "multiple resources" or from the "undifferentiated capacity" perspectives. This treatise will be dedicated to those aspects of methodology and data analysis which transcend these problems in the current literature.

In the discussion that follows, the present authors provide a simplified model of the hypothetical T/S ability factor, which is consistent with a wide range of general a priori expectations. In a future paper, we will develop a more specific model which takes particular theoretical orientations into account (i.e., "multiple resources" vs. "undifferentiated capacity", and practice).

One of the most fundamental conclusions about individual differences is that there are few (if any) truly orthogonal cognitive abilities. Based on discussions and massive amounts of data (Humphreys, 1979; McNemar, 1964; Spearman, 1927), it should be recognized that for all intents and purposes, all tasks which show consistent individual differences and require use of cognitive faculties will be positively intercorrelated (though in many cases, such correlations will be small in magnitude -- depending on the relative communality of respective task features; see Thomson, 1951). Although there is always substantial controversy surrounding the nature of intelligence, it is appropriate (and parsimonious) to integrate the data of universal positive intercorrelation of cognitive tasks as representative of some general intellectual ability (Humphreys, 1979).

However, the pervasive influence of general intelligence is not so great as to obscure the useful consideration of specific abilities such as verbal, spatial, mechanical, etc. Such constructs are important, though researchers should note that these abilities are not statistically independent in the population (see Vernon, 1961). In view of this fact, theories regarding a hypothetical T/S ability should also be constructed within a general cognitive ability framework. In other words, an ability to do T/S tasks would be expected to be related to other cognitive abilities, though it may explain a meaningful portion of the variance in subjects' performance levels.

Therefore, one would expect the T/S ability to be moderately correlated with whatever range of component tasks one might want to consider in any experimental design. However, the key to the utility of the factor is that the T/S ability, per se, is not uniquely associated with any single task performance, but rather is more commonly associated with all (or many) dual or complex tasks which require subjects to perform several cognitive operations at once. In addition, the T/S ability should not be highly associated with any particular aspects of complex tasks which are peculiar to specific input or output modalities, continuous or discrete response requirements, and so on.

In order to provide a useful reanalysis of the studies under discussion, it is necessary to indicate what an appropriate model of a T/S ability might involve. The model considered below is consistent with many a priori expectations in this area. However, we have refrained from either choosing a particular theoretical position with respect to information processing or making ad hoc changes based on the a posteriori nature of the data analysis (except as noted), since these topics are tangential to our main thesis.

The major tenet of the model of T/S presented here is that the distribution of dual-task performance scores may be partitioned into three specific sources of between-subject variance. These represent (1) and (2) -- the ability distributions for each of the respective single task performance scores, and (3) the distribution of T/S ability (i.e., scores on a hypothetical latent trait concerning doing two tasks at once).

If, for the sake of clarity and simplicity, these three abilities are assumed to be independent of each other, then it is a reasonable premise to accord 37.5 percent of the joint dual-task score variance to be attributable to each of the component single tasks (i.e., a subtotal of 75 percent of the variance), leaving the remaining 25 percent of the score variance attributable to the T/S ability. (We have assumed a situation of error-free data with perfect reliability of measurement.) The assumption underlying this partitioning of the variance is that dual-task performance, regardless of the presence of a T/S factor, must be determined to a great extent by the component tasks.

To illustrate the nature of this assumption, think of the following situation: If one is willing to accept the utility of considering linear relationships (i.e., Pearson correlations), then a zero correlation between a dual-task score and a component single task performance score would

indicate that the poorest performers on the single tasks would have a probability of performing well in the dual-task situation equal to that of the subjects that performed best on the component single tasks (in absolute performance level -- not relative performance decrement). This appears implausible. If some T/S ability exists, subjects of equal or equivalent single task performance levels will be expected to differ in their respective abilities in the T/S situation; but subjects that differ greatly on single task performance will likely also differ greatly in performing such tasks concurrently as well. In fact, this is the claim made explicit with this discussion of the hypothetical ability. The T/S ability, therefore, will only partially determine dual-task scores. Measurements of a T/S ability trait would be expected to correlate $r=.50$ with dual-task scores while remaining independent of single-task scores (i.e., $r=.00$).

Use of Factor Analytic Techniques. Given the T/S ability model discussed above (i.e., 25% of dual-task score variance-accounted-for) or one similar in structure, it is logical that correlational studies be implemented in order to demonstrate the existence of this ability. The proposed pervasive nature of the simplified model of the T/S ability suggests that any selection of combined single tasks will result in scores partially determined by subjects' T/S ability level. However, evaluation of the presence of this ability is dependent on separating score variance attributable to the single tasks, the T/S ability, other intervening variables, and errors of measurement.

Given this wide range of considerations, the factor analytic procedure is appropriate for the investigation of components and magnitudes of common variance expressed in task score intercorrelations. The difficulties with "eyeballing" the data, given the number of features that the model specifies as necessary for comprehensive quantitative evalution, make the use of such multivariate techniques a virtual necessity (See reference note 1). However, as will be illustrated below, competent inferential use of factor analysis requires a substantial amount of a priori structure specification on the part of the experimenter.

Several facets of factor analytic procedures and techniques will be discussed in the sections that immediately follow. Each of these issues is crucial for consideration by researchers before any study using factor analytic procedures is implemented. These are: 1) Decisions about the number of factors; 2) Requirements concerning numbers of subjects, and numbers and types of variables; 3) Rotation of factors; 4) The choice with respect to use of Orthogonal or Oblique factor structures; and 5) Exploratory versus Confirmatory factor analyis techniques. Each will be discussed in turn below.

1. Number of Factors. One of the initial choices the user encounters when performing a factor analysis is the decision of how many factors to retain for further analysis and rotation. Aside from obvious mathematical constraints (i.e., the number of factors cannot exceed the number of variables in the analysis), and other statistical considerations (number of subjects and variables will be discussed in section 2), no infallible specification method is available for use. However, a number of methods are available and are readily applied when a user so chooses. Choice of any or

all of these methods involves an implicit agreement with the assumptions underlying the method or methods in use. On the other hand, the user may specify the number of factors of interest a priori.

Probably the most commonly used method of determining the number of factors to retain was created by Kaiser (1958). This method specifies that the user initially perform a Principal Components Analysis (i.e., values of unity in the diagonal of the correlation matrix) and choose to complete a factor analysis using only the same number of factors as there are eigenvalues greater than 1.0. The rationale for this method, as Harmon (1976) points out, is "plausible since the sum of all n roots is precisely n, so the value of one is merely par and surely if another dimension is to be added it would be desirable to have it account for at least an average contribution." However, a review of the psychometric literature finds much criticism to accompany this "easy-to-use" method (see Humphreys & Ilgen, 1969); since its use often results in erroneous judgments when the underlying factor structure is a priori known.

Other methods have also been proposed to aid the researcher in the decision about number of factors to retain. One method includes the use of Maximum Likelihood techniques for establishing a method for this decision (see Mulaik, 1972). This method allows the user to decide on what a minimally "significant" amount of variance accounted for would be for a given factor solution, and the procedure yields a solution based on the likelihood of the factor's given "significance".

Another commonly implemented method was developed by Cattell (1966) and is known as the "Scree Test for the Number of Factors". This is ostensibly a more subjective method, but it has some desirable heuristic qualities. To use this test, the user needs to plot the latent roots of the raw correlation matrix (i.e., unities in the diagonal) against the rank of the respective roots. Based on determining where subjective "breaks" and "elbows" occur in the pattern of descending eigenvalues, the user determines where the distinction can be made between the steep descending curve of highly significant factors and the line of "trivial" or non-significant factors which form the asymptote of the curve.

While Cattell's Scree test is elegant in its formulation, and Kaiser's "eigenvalues greater than 1.0" criterion is simplicity in its use, the psychometric literature indicates a much more useful and rigorous method is available that should be recommended over, or in addition to these techniques; that is, the method of Parallel Analysis (Humphreys & Montenelli, 1975; Montenelli & Humphreys, 1976). This method has been developed with the use of Monte Carlo procedures and has both statistical and empirical evidence to its general superiority over other methods, including the Maximum Likelihood method. The rationale behind this method is that, for any given number of variables and number of observations (i.e., subjects), randomly generated data may be constructed contingent upon the sampling characteristics of the factor analysis input matrix (i.e., usually intercorrelations with some estimate of communality for each of the variables). This random data matrix may then be analyzed in "parallel" with the "real" data matrix under consideration, and their respective latent roots compared. When values in the series of descending

real roots no longer exceed the corresponding random roots in magnitude, that point indicates when the addition of more factors usually becomes counter to utility and parsimony. Factoring beyond that point raises doubts due to the small probability that such factors represent anything except the influence of random relations due to measurement error.

While several studies have supported the use of this method, it is not an infallible procedure for the determination of the number of meaningful factors underlying a particular data set (Humphreys & Montenelli, 1975). Under specific conditions such as cases when the common factor model is inappropriate and samples are large, errors may occur; though the method still remains superior or equal to the other methods.

The major point to be made is that any method chosen for determining the number of factors has a set of underlying assumptions, which may be at odds with the user's intentions, and no method certainly has universal support in the psychometric literature.

2. Choice of variables and subjects: From a factor analytic approach, the number of variables used as input sets the upper bounds on the number of factors which are statistically overdetermined for a given analysis. In general (see Mulaik, 1972 for a table of actual values), a rule of thumb exists that the user should incorporate at least three variables to jointly determine each factor that is desired for derivation. This, of course, assumes that the user has a priori knowledge as to the nature and interrelations of the variables under consideration, so that information as to which variables will determine which factors is known.

Choice of variables that are highly correlated with one another indicates that they will ordinarily provide the analysis with joint determination of single factors. However, when variables are moderately correlated with one another, their inter-relationships are much more difficult to interpret (as discussed below with respect to the concept of simple structure), and may give indications of correlated abilities (or factors) -- thus complicating the resulting factor solution. While adding more and more variables will allow additional safety in overdetermination of factors, this solution will introduce logistic problems concerning the required additional number of subjects.

The choice of the number and types of subjects for a given study should be guided by the choice of the number of variables and the refinement of the experimental questions. In general, the stability of the correlations between variables will be moderated by both the number of subjects and the range of their abilities. When the range of ability is severely restricted (such as in a college population) correlations are certain to be attenuated, thus obscuring the underlying interrelationships in the general population (see McNemar, 1969). When the number of subjects does not exceed (by about 10 times) the number of variables in a factor analysis, the stability of the solution (and thus useful generalizability) will be hindered. Therefore, the nature of the relation between the number of variables and the number of subjects must be kept in mind for a successful factor analysis. When small numbers of subjects are used, it is often necessary for the investigator to estimate the validity of, or

cross-validate, the results of the study -- just as is the situation with use of other multivariate methods, such as multiple regression (see Armstrong, 1970).

3. <u>Factor Rotation.</u> Another basic problem in the use of factor analysis, after determining the number of factors, is the issue of rotational indeterminacy. The problem is that for any factor solution (having more than one factor), there is a virtually infinite number of rigid rotation-reflections that will provide exactly the same reconstructed correlation matrix.

Historically, psychometricians have attempted to deal with this problem by designing heuristically motivated methods for use in deciding the "appropriate" or most psychologically meaningful orientation for factor structures in general. Thurstone's original conception of such a universal criterion of parsimony and meaning was termed "simple structure", and it included a specification that no variables load on all of the factors (see Harmon, 1976). During the 1940's and the 1950's a number of analytical, as well as objective specifications were discussed for use in the determination of "simple structure".

One contribution in this area was made by Tucker (1955). With respect to simple structure, Tucker specified a distinction between exploratory studies and those of a confirmatory nature. He stated that:

> "In exploratory studies [as opposed to confirmatory ones] a fully determined simple structure solution should not be expected and rotation of axes will probably be continued on subjective bases. There may well be attempts to maximize the number of small, insignificant factor loadings; but some attention may also be given to interpretive possibilities." (p. 210).

Developments by Carroll (1953) and Neuhaus & Wrigley (1954) brought about an early computationally determinate rotational procedure called Quartimax. Without going into the mathematics of the procedure, it suffices to reiterate Kaiser's (1958) description of the end result of the procedure. The method seeks to "simplify...each row (variable) of the factor matrix. The implication of this is that the Quartimax criterion will often give a general factor." (p. 190).

The most commonly used orthogonal rotational procedure is the Varimax criterion, which was developed by Kaiser (1958) in response to the Quartimax criterion. This method has the effect of "simplifying" the columns (i.e., factors) of the factor matrix rather than the rows. "Simplification" is taken to follow from the proposition that factor loadings of unity (i.e., plus or minus 1.0) infer a "functional relationship," loadings of zero magnitude infer "no linear relationship"; and that these types of loadings are considered to lead to most easily interpretable (or "simple") factors. In comparison, moderate factor loadings lead to factors that are "most difficult to understand".

Therefore, in practice, the Varimax Criterion rotational procedure will rotate any given factor solution away from so-called "complex" factors(i.e., those that have moderate loadings), since rotations towards unity and zero loadings which will tend to maximize the Varimax Criterion statistic. As one might expect, for many types of exploratory studies, this procedure is desirable for "simplified" factor interpretation. On the other hand, if a researcher has any interest in complex factors -- and thus variables "which have loadings on many or all of the common factors", the Varimax procedure will at best obscure the factor solution; and at worst, fallaciously lead to conclusions that the factorial structure of interest is disconfirmed by the data. (Further discussion of this issue will be presented when the dual-task literature is reviewed.)

However, if the researcher wishes to take Tucker's (1955) suggestion for subjective rotation in exploratory analysis, there are a number of options available. For small number-of-factor solutions, graphical rotations often can be very useful (see Carroll, 1980). In addition to paper and pencil techniques, there are a number of computer-aided interactive graphical rotation programs available for use. However, when the number of factors exceeds three or so, these methods become somewhat cumbersome. In addition, their successful use is more often a statement of the artistic ability of the researcher, rather than a statement about the heuristic utility of the underlying factor structure.

Another subjective method for exploratory rotations of factor structures, and one considered useful by the authors for the type of studies under discussion in this report, is the Procrustes rotational procedure (see Mulaik, 1972). For early stages of model development and experimentation, this technique has a number of advantages. In addition, it is as simple to use (in computer packages) for any number-of-factors solution.

In detail, the procedure is loosely analagous to the actions of the mythical innkeeper for which it is named. The paradigm involves the following steps: 1) The user chooses a factor solution of interest as a "target" -- such as the model presently under consideration (i.e., there are no "simple structure" constraints imposed by this method). 2) The original factor matrix (regardless of orientation) is then used as input to be rotated. 3) The computer algorithm (from which several similar methods are available -- see Schonemann, 1966) iterates so that the closest (usually by a criterion of least squares) rotation of the factor matrix to the target matrix is found. 4) Both the rotated factor matrix and the residuals (i.e., the differences between the target and the closest rotation of the actual data) are then available for analysis and evaluation. Here, the procedure involves the examination of similarities and dissimilarities between the most favorable representation of the data and the model under consideration. In addition, the researcher may repeat the procedure with any additional model factor structures as targets.

On the other hand, Procrustes procedures serve as a double-edged sword. Even though the mathematical integrity of the rotated factor matrix is maintained (i.e., the fit to the raw correlation matrix is the same), the procedure which determines the rotated solution has capitalized on

chance relationships in the factor matrix, in a manner that is specifically under subjective control, as opposed to the "objective" nature of, say Varimax, Quartimax, etc. The reason that Procrustes procedures are considered more subjective than, say, Varimax and Quartimax, is that all of the factor loadings of the target are specified in Procrustean analysis; while only the general form of the factor structure is assumed for maximizing the Varimax or Quartimax criterion. The investigator has no direct control of the relationships between specific variables in the use of the simple-structure-seeking procedures; only that loadings on factors in general will tend towards unity and zero. In the Procrustes situation, evaluation of the actual underlying "psychologically meaningful" structure represented in the rotated factor matrix can be problematic (see especially Horn & Knapp, 1973; also Humphreys, Ilgen, McGrath, & Montanelli, 1969). The major benefits in this method lie in the fact that researchers do not have to be constrained to the arbitrary and often inappropriate demands of "objective simple structure" criteria. Coupled with conservative interpretations, appropriate use of Procrustes rotations can provide information to the researcher, as well as opportunity for model development.

4. Orthogonal and Oblique Structures. Once the number-of-factors question has been settled for a particular data set, the investigator has another option in addition to the orthogonal rotations described above. The use of oblique (or correlated) factors is often more appropriate for the model-theoretic approach in data analysis. For instance, if several single tasks are used in dual-task paradigms which are moderately or substantially intercorrelated with each other and each single task is considered to define a factor; then it would likely be counterproductive to attempt to fit the data to an orthogonal factor solution. Use of an orthogonal procedure in this case will result in a muddled structure, in which the single tasks will necessarily be associated with more than one factor each (i.e., complex variables -- much like the dual-task variables). These will generally not be conducive to parsimonious description.

On the other hand, use of oblique factor analysis has a number of drawbacks for both the naive and the experienced user. In the first place, the fit to the data (from a strict mathematical point of view) is exactly the same for both the orthogonal and the oblique factor solutions. Second, the factor pattern (the loadings of the variables on the factors) and the factor structure (the correlations of the variables with the factors) are identical for the orthogonal solution (thus the single factor matrix); but differ from each other in oblique solutions. Finally, an interpretation of the oblique structure necessitates the joint consideration of the factor pattern and the factor intercorrelation matrix (since, by definition, factors are not constrained to be uncorrelated as in the orthogonal structure).

Consideration of this issue is important to the selection of variables for use in a study of individual differences in time-sharing ability. When models can be specified in great detail, the complications arising from working with oblique structures are somewhat diminished since the use of

strictly confirmatory factor analytic methods may be implemented (see discussion below). When the user has few a priori expectations, it is likely that the costs of attempting to fit and reliably interpret both factor structure and factor intercorrelation solutions will override any gains in information from the oblique solution.

5. Exploratory versus Confirmatory Factor Analysis. There is a nebulous distinction between those studies that make exploratory use of factor analytic methods and those which use the methods in a confirmatory manner. Indeed, these catagories define endpoints on a continuum, rather than a dichotomy. However, it is clear that no factor analysis is ever completely exploratory in method, as the researcher must at least select the variables of interest for input. The location of any particular factor analysis in this continuum is at least partly determined by the amount of prior knowledge about both the input variables and the underlying structure of the data.

Bringing expectations to the analysis based on experience, theory, hunches, etc., is no different from use of those expectations that are necessarily involved in planning and designing any experimental procedure. Just as a failure to control for some possibly influential variable can lead to criticisms regarding confounded results, failure to take characteristics of factor analysis into account can lead to illusory results and erroneous conclusions. When a researcher has a priori expectations, a large amount of guesswork and artistic technique in factor analyzing data can be circumvented.

Over the last several years, a number of developments have taken place in the area of multivariate model testing. The latest example of this type of methodology is LISREL IV, (Joreskog & Sorbom, 1978), which provides an "Analysis of Linear Structural Relationships by the method of maximum likelihood." Both orthogonal and oblique factor analysis models are subsumed by this algorithm, which provides for a broad range of other models as well.

Implementation of this analytic approach requires that the researcher painstakingly specify or otherwise constrain various parameters believed to underlie the data structure. The LISREL algorithm then provides for a maximum likelihood estimation of the remaining parameters. Finally, a goodness-of-fit statistic is calculated relating the chosen hypothesis model and the closest iterated structure based on the input data. The fit statistic can then be used to aid an evaluation of the researcher's confidence in the representation of the data, based on the initial hypothetical model. The researcher using confirmatory factor analysis must satisfy a number of statistical and inferential requirements to interpret the output of the analytic precedure.

First of all, the requirements regarding variables, subjects, and so on are essentially unchanged in this type of analysis. Next, the determination of the number of factors falls outside the specific method, and as such, must still be solved a priori or by use of methods based on the data. In addition, the specification of the model under consideration is crucial to the method. If only one model is investigated, the analysis

gives a veridical probablistic statement that the data and the model are coincidental. However, when the model is revised from the determined discrepancies between the data and the model, a veridical evaluation of the likelihood of the revised model must take the post hoc (or Bayesian) nature of the ensuing investigation into account. As the number of model revisions increases (in order to arrive at an adequate fit of the data), the researcher's confidence in the model must decline rapidly.

The other issue that will affect the outcome of the analysis concerns the number of parameters the researcher allows to be fit by the analytic procedure. As the number of these parameters increases, the less the parsimony and the utility of the model (i.e., the fixed or constrained parameters). In general, the value of confirmatory factor analysis is bounded by the researcher's ability to use information previously determined about variables and their interrelationships to test logical extensions (not of a major proportion) beyond a firm foundation of an underlying data structure. The final evaluation of any particular theoretical issue would be appropriate for this type of analysis. In the T/S ability domain, this will occur only after single-task ability interrelations and single to dual-task relations are well determined.

In summary, the major point to be made in reference to this variety of techniques is that their successful use is crucially dependent on the a priori specificity of the data structure, as well as on the statistical sophistication of the user. However, such types of analysis are of importance once the relevant exploratory work on an issue has been completed and models are available for testing -- or for choosing between.

Simulation

Given the considerations discussed so far, a contrived data set was created to show graphically how these issues influence the results of research on the hypothetical T/S ability. First, an a priori factor structure was created, based on a hypothetical dual-task experiment (see Table 1). The structure represents the following hypothetical experiment and characteristics of the data: 1) Four independent (i.e., uncorrelated) single tasks were created. They are denoted as A, B, C, and D respectively. 2) All paired combinations of the single tasks were also administered. These dual-tasks are denoted as AB, AC, AD, BC, BD, and CD. 3) Each task was also paired with itself (i.e., identity pairs). These dual-tasks are denoted as AA, BB, CC, and DD. 4) To make the demonstration more powerful, the data are constrained to be measured without error, so the relevant intercorrelations between the tasks represent the theoretical underlying relationships, and the tasks themselves are also constrained to have perfect reliability (i.e., excluding all of the possibly obscuring effects of, say, "structural interference," subject motivation, fatigue, data or resource limitations of the tasks, etc.)

Since the single tasks were constrained to be statistically independent, each single task was conceived to uniquely define a separate orthogonal factor. In other words, four factors in the solution represent the respective single task abilities. Each dual-task distribution of scores

had the following characteristics, based on "equal allocation of task priorities" type of instruction: a) Of the total variance, 37.5 per cent was attributed to the first component task; b) An identical 37.5 per cent of the total variance was attributed to the second component task; and c) The remaining twenty-five per cent of the variance was attributed to the dual-task or T/S factor. As a result, each dual-task has a .50 loading on the T/S factor (see Table 1). In this manner, each of the dual-task scores will be uncorrelated with the single tasks which are not themselves components of particular dual tasks. This can be seen from an examination of the reconstructed score intercorrelation matrix in Table 2.

Given this contrived data set, it is apparent that there are five factors of interest underlying the input correlation matrix (see Table 1). (As the latent roots indicate, determining the number of factors from the number of roots larger than 1.0 will result in underfactoring (see Table 3.). Thus the use of Kaiser's rule of thumb in this case would have the effect of determining that the time-sharing factor is not supported by the data.) Since these data represent that of a population, the Parallel Analysis criterion for determination of the number of factors, can be used with some arbitrarily large value for the number of subjects parameter (e.g., 10,000). Results from this type of analysis are in agreement with the correct number of predetermined factors. In addition, the Scree Test would also give a veridical result for determination of the number of latent factors since the values fall in a manner such that the fifth root represents a value above the last run of steady (or steadily descending) roots (see Figure 1).

However, the prior knowledge about the actual rank of the correlation matrix would have enabled the user to bypass the number-of-factors issue. The correlation matrix was factored into principal factors with the Minres method (see Harmon, 1976), and is presented in Table 4. This particular structure represents the dimensions that maximize the amount of variance accounted for by the factors, but is just one of an infinite number of possible rotations of the factor solution. For the purposes of psychological inference and description, of course, such a configuration provides little information to the researcher, since such solutions generally indicate complex factors, rather than rotations to more meaningful or "simple" structures. (One should note that if the variables could be plotted in the factor space, the particular rotations would not be as necessary for an investigator to understand the interrelationships between the variables. With many variables, or with more than three factors, it is easier to understand the structure with tables of loadings. So-called rotations to parsimonious simple structures are performed to facilitate such evaluation -- as the reader may see from the comparing Tables 1 and 4.)

A fatal error that could be made in the rotation of this solution for maximal psychological interpretability would be to subject it to a Varimax procedure (or any other arbitrary procedure that seeks to give only large and near zero loadings on the factors). To illustrate the effect of such a procedure on these data, the results of a Varimax rotation are shown in Table 5. Notice especially how the solution differs from the original structure which was created for this demonstration (Table 1). If an

investigator attempted to interpret this Varimax solution, he/she might be tempted to discard the fifth factor, since there are no moderate or large loadings on it. If each of the first four factors were to be interpreted as representing the four single task abilities respectively, one might conclude that some time-sharing factor is present, even though it only accounts for less than 7 per cent of the total score variance for each of the tasks (which is indicated by examining the fifth factor). In that case, the topic might be discarded as one of a trivial nature.

However, contrary to the Varimax solution, the time-sharing factor did exist in the original data. The underlying relationship that shows that 25 per cent of the variance of each of the dual task scores can be attributed to this factor was known prior to the analysis. If a Procrustes procedure were used, where the target is identical to the model which generated the data, the original structure would be perfectly recovered (i.e., Table 1). Even if the Procrustes target differed somewhat from the contrived model, it is likely that the investigator would come much closer to realizing the true nature of the underlying structure of these data.

When a priori information and theory lead the investigator to conclude that task factors and/or the T/S factor can not be reasonably represented as statistically independent hypothetical constructs, then an orthogonal factor analytic solution will be inappropriate. However, the difficulties of incorporating factor pattern, factor structure, and factor intercorrelation matrices into data analysis and interpretation, make the use of oblique factor solutions a more involved task. The final result is the addition of another (infinite) number of possible solutions to the indeterminacy of the rotational solution of the factors, this family containing a variety of different factor intercorrelations, etc.

This is not to say that such a situation makes the data analysis problematic. Oblique Procrustes, Confirmatory, and Simple-Structure seeking rotational procedures are all available for general use. The additional specification of parameters involved with confirmatory and some exploratory methods of factor analysis, should not present great difficulties, given the types of information that should be available for the investigator to make such a priori decisions about the model.

If the structure underlying the data is not orthogonal, the degree to which an orthogonal solution is illusory is generally related to the degree to which the factors themselves are correlated. When task factors are correlated to a small degree, use of orthogonal techniques is acceptable, given considerations of parsimony. To illustrate this type of case, a simulation was created with the hypothetical task-factors interrelated $r=.4$. The resulting analysis indicated that an orthogonal model Procrustes procedure overestimated the loadings on the T/S factor by about 7% of the variance. Both orthogonal and oblique simple-structure-seeking procedures (Varimax and Direct Oblimin, respectively) on the other hand severely underestimated the loadings on the T/S factor (by around 15% -- i.e., loadings of approximately .30). If the task factors correlate to a larger degree, the loss of parsimony in the orthogonal structure will be seen as increased complexity of the factors (i.e., lack of simple structure).

However, one must not loose sight of the fact that such simulated data are "cleaner" than data one might generally collect. In order to consider expectations with respect to particular abilities and their respective contributions to variability in common laboratory settings (i.e., fallible data), attention must be devoted to aspects of task reliability, practice effects, restriction of range in the subject population (e.g., the use of college sophomores or armed forces recruits) and issues relating to "data limited" or "resource limited" tasks (see Norman & Bobrow, 1975). It is crucial for an experimenter to predict such effects, so that data structure consequences may be considered, and further analyses planned appropriately. Making use of the discussion in this paper depends on this type of reasoning.

Review of the Literature

In view of the methodological and data analytic discussions above, an evaluation of the evidence regarding the time-sharing ability must involve a critique of the literature that has addressed this issue. The studies that have employed correlational procedures in addressing the issue are those of Jennings and Chiles (1977), Sverko (1977); Hawkins, Rodriguez, and Reicher (1979); and Wickens, Mountford, & Schreiner (1979 and 1981). An experiment by Damos & Smist (1980) which has been somewhat concerned with this topic area, but makes use of an experimental rather than a correlational approach, will be reviewed with respect to these earlier discussions.

The study by Damos and Smist (1980) provides an important contribution to the discussion of the hypothetical T/S ability for two reasons. Briefly, the authors differentiated subjects with respect to type of response style -- or response strategy used, rather than considering subjects only as they differ in absolute levels of task performance. Second, Damos and Smist used an established method (see Jones, 1972) in selecting for analysis, only data which were determined to have stabilized (i.e., that contain no spurious practice effects).

However, their investigation had problems resulting from the small number of subjects (N=11), an analysis which contained combinations of difference scores from several dual-tasks and raw scores from another task, and so on. As a consequence, their findings do not provide adequate evidence for or against the existence of the type of T/S ability under discussion in this paper. On the other hand, investigations of this type are complementary, given that both qualitative differences in subjects' response-styles and quantitative differences in performance levels may be important to understanding the nature of T/S processes.

<u>Jennings and Chiles (1977)</u>: The study by Jennings and Chiles has often been cited as indicating the existence of some time-sharing ability. However, based on the considerations mentioned above, several problems lead to questions about the validity of the authors' conclusions. First, the authors retain variables that show little or no reliability of measurement (four variables had reliability coefficients of 0.000, 0.005, 0.279, and 0.218 respectively -- none accounting for more than 8 percent of the common variance in scores). The effect of including such variables in a factor

analysis is to obscure any underlying relatedness with other variables, and to generate an a priori violation of the common factor model.

Second, when the number of subjects (N=39) is not substantially larger than the number of variables (n=22), factor solutions have little stability and thus are not likely to be replicable. Third, the authors report significant practice effects "for seven of the eleven measures" (each of the measures was given in simple and complex form); and significant Treatment X Practice interaction effects on two of the measures. As pointed out earlier, and emphasized by Damos and Smist (1980), such practice related performance changes confound the determination of differences in abilities, skills, or in benefit-from-practice within the sample.

Because the factor analysis included these problems, employed: 1) the eigenvalues greater than 1.0 criterion, and 2) a Varimax rotational procedure; no critical reanalysis could provide information for the topic under discussion. In addition, there was a failure to construct an appropriate model that took the reliabilities and practice effects into account as well as issues pertaining to asymmetries in tradeoffs between tasks, instructed strategies, and single-dual task correlations; the data do not provide an interpretable test of the existence of the T/S ability.

Sverko (1977): The study by Sverko was similar to that of Jennings and Chiles in many ways regarding data analysis. The author utilized a design in which subjects were tested on four different single tasks and then performed the dual-task combinations of those single tasks (identity-task combinations were not used). The subjects' concurrent performance was measured for each of the component tasks in the dual-task paradigm, though no joint measures from performance on both tasks were derived for the first stage of data analysis.

Subsequent to the experiment, the author wanted to investigate the presence or absence of some ability that transcended the dual task combinations of the four single tasks in question. Instead of deriving joint scores (i.e., determining some overall dual-task performance level for each subject on each task-pair), or taking account of trade-off asymmetries in formulating a specific underlying model of the T/S ability, Sverko intercorrelated all of the raw scores from the single and dual tasks and then performed a Principal Component analysis. (Recall that the difference between component and factor analysis is that component analysis makes use of unities in the diagonal -- thus avoiding the estimate of communalities -- but instead involves further difficulties in interpretation. See reference note 2.)

Given the aim of the research project (i.e., to demonstrate that a T/S factor underlies individual differences in dual-task performance), Sverko should have designed model structures based on an appropriate null hypothesis for testing purposes. However, three major limitations are evident: a) not taking asymmetric tradeoff of performance in task combinations into account; b) using principal components analysis when factor analysis was appropriate; and c) using the Binormamin criterion (an oblique simple structure seeking procedure -- similar in effect to Varimax

in that it attempts to maximize large loadings and zero loadings). Together these limitations result in a "test" where no difference would exist between a priori probabilities of the outcome of the data analysis and the a posteriori analysis of the derived structure.

On the other hand, the decision to initially make use of a five component analysis was in Sverko's favor. He found that the fifth factor did not have a latent root larger than 1.0, and that the component only accounted for approximately four percent of the total common variance (of course, the simulation illustrated in this paper found similar contributions to accounting for total variance when a time-sharing factor did underlie the data). Given Sverko's analysis with respect to a four component (or factor) solution, based on use of four single tasks that were not substantially intercorrelated; it should be apparent each of the components defined by the tasks would account for more variance than a potential T/S "factor". Since the statistical procedure is such that components are extracted in order of their influence on the correlation matrix, the decision to only take four components would likely result in a representation of only the influence of the single tasks. In retaining only four factors, no reasonable assumption would imply that a T/S ability be represented. Instead, if the T/S ability did exist, its influence would be found in the residual variance left unaccounted for.

A second stage analysis involved computing "Total Decrement Scores" for the subjects in the dual-task situations. In keeping with the previous literature, Sverko incorporated the method as follows: " D = (S - T)/ S , where S = solitary task performance, T = time-sharing performance of the same task, and D = time-sharing decrement score *reflecting the percentage* of solitary task performance lost under time-sharing conditions (p. 17)." He found that the three correlations between tasks that did not share components, all had magnitudes near zero. However, as Wickens, et. al. (1981) have shown (and will be reviewed later in this paper), there is a very complex relationship between individuals' initial single task performance and dual-task difference scores. This point indicates that use of such techniques does not effectively "partial out" the single task performance level influences from dual-task performance.

In conclusion, a more suitable reanalysis using raw data would be needed before a final evaluation of Sverko's results can indicate appropriate evidence for or against the existence of a time-sharing ability.

Hawkins, Rodriguez, and Reicher (1979): This study is another example of design and analysis problems that obscure a useful investigation of the hypothetical time-sharing ability. In this paper, the authors describe a paradigm that differed somewhat from that of previously discussed studies. Here, the selected single tasks were all basically the same; what differed from task to task were a) difficulty levels, b) input modalities, and c) output modalities. In addition, in dual-task situations, the subjects were instructed to maintain single-task-level performance on one task in the task pairs and to consider the other designated task as a secondary task. Hawkins, Rodriquez, and Reicher based their interpretations on the performance levels of the secondary tasks.

Two basic problems exist for interpretation of their data. First, only the correlations across the dual-tasks are reported; i.e., the single-to-dual task correlations and the single-to-single task relationships were not presented for consideration. Second, evaluating correlations based on only 18 subjects is extremely problematic, especially when subtle effects are under investigation; since the sampling distributions of the correlations are so broad.

The authors concluded that the mean values of the secondary task inter-correlations provided evidence for a single underlying factor of individual differences in ability (p. 10). In order to investigate this statement, we reanalyzed the data set under discussion. A Parallel Analysis was performed on the latent roots from the matrix of correlations (with squared multiple correlations in the diagonal entries -- as estimates of communalities). The findings indicate support for their conclusion (see Table 6). However, given that these dual-task scores were so highly intercorrelated, it is reasonable to also assume that the single tasks as well had correlations near unity (since the tasks only differed in input modality, output modality, and difficulty). Based on the discussion in previous sections of this paper, if only one single task ability is the determinant of dual task performance, then it should be expected that the individual differences on this ability will far outweigh the T/S ability differences. Unless single task performance scores were entered as variables in a factor analytic procedure (as so-called "marker variables"), it would not be possible to determine the relevant amount of residual variance in correlations between tasks that would be assigned to the T/S ability. In this case, using the single tasks as markers would be crucial for any critical evaluation of the dual-task data.

<u>Wickens, Mountford, and Schreiner (1979, 1981)</u>: Although this experiment shared many of the characteristics of the Sverko (1977) study, several considerations taken by the authors made the data more appropriate to the assessment of the time-sharing ability issue. While the analyses devoted to the T/S issue in their study were not appropriate for proper evaluation, as in the other studies discussed above; the design was sufficient and the raw data were available. Therefore, an intensive reanalysis was performed by the present authors. A detailed discussion of the results will follow a review of Wickens, et. al.'s method and findings.

Briefly, the following experimental procedure was employed. Four single tasks were chosen for use in the study: 1) Tracking (T), 2) Classification of numbers (C), 3) Spatial judgment of line orientation (L), and 4) Auditory running memory of letters (A). These are described in detail elsewhere (see Wickens, et. al. 1979; 1981). Forty subjects participated in the three day experiment which involved performing all four of the single tasks, each task simultaneously paired with itself -- the identity pairings -- (except for the Auditory task), and each different pair combination of tasks. This resulted in thirteen different tasks (1-T, 2-TT, 3-TC, 4-TL, 5-TA, 6-C, 7-CC, 8-CL, 9-CA, 10-L, 11-LL, 12-LA, 13-A). Each of the non-identity task pairings had separate scores on respective component tasks, which resulted in 19 raw score variables. (The identity task pairings, i.e., TT, CC, and LL were each given only composite scores, since no useful distinction could be made beween respective component task

scores.)

At this point, practice effects, reliability measures, and single-to-single task correlations are important to consideration of the factor solutions. In some sense, the presence of practice effects obscures the relationships among the variables, since the day-to-day reliability measures place a lower bound of the underlying correlations between tasks. Since these measures range from moderate to good (for single tasks, the reliability coefficients were as follows: r = .69, .89, .75, and .81, for Tracking, Classification, Line Judgment, and Auditory tasks respectively), the utility of further analysis is not necessarily ruled out (as was the case for some of the Jennings & Chiles data). On the other hand, the single-to-single task correlations are a cause for concern with regard to expectations of simple orthogonal factor structure (see Table 7). The substantial correlation between the Classification task and the Line Judgment task (r=0.63) lead the present authors to believe that these two tasks together define only a single factor. (This was a post-hoc conclusion.) In addition, Auditory task performance is moderately related to Tracking and to Classification task performance, probably giving rise to a somewhat oblique structure (though the degree of correlation may not be such that it precludes some general analysis at the orthogonal level).

In terms of identifying the underlying structure for the entire range of tasks and task combinations, it would be expected that factors for T, A, C & L together, and the T/S ability would all be autonomous entities defined by stable individual performance level differences. It is therefore appropriate to adopt this type of structure as a reasonable null hypothesis, and so set out to reject the model; with special attention to the factor of interest -- the T/S ability.

The authors provided an extensive evaluation of the time-sharing efficiency parameters of the dual task combinations. However, the two analyses concerning time-sharing abilities did not take sufficient account of these data. The first analysis performed by the authors was a factor analysis with the following 8 variables as input: the four single task performance scores, and mean values across all performance measurements for each of the four tasks performed in all the dual-task combinations (e.g., T-dual was represented by the TT, T(C), T(L), and T(A), scores averaged for each subject).

While two-factor and three-factor solutions were both derived and provided for inspection by the authors, it is apparent that a four factor solution would be completely underdetermined by only eight variables. As expected (especially with simple-structure seeking rotations), the three factor solution shows the dominating of influence of the single tasks, with the C and L variables jointly defining a single variable (see Table 8). However, it is not possible to assess the presence or absence of the time-sharing ability, given the small number of variables and the possible obscuring influence of averaging over the dual tasks. Indeed, even if it were possible to assess the T/S ability with this selection of variables, the simple-structure seeking method of factor rotation used by the investigators would have also obscured the determination of the factor (see simulation for examples).

For the second analysis, Wickens, et. al. adopted a procedure for use of a variant of difference scores for arriving at component task scores, and a method for determining joint scores for each of the dual-task combinations. There are several ramifications from these procedures as have been discussed in previous sections. Nevertheless, the analysis went as follows: Dual task "normalized decrement scores" were computed by subtracting each subject's dual task component score from the subject's single task score and dividing the score by an average within-subject variability measure (as the authors describe the variability measure --

> "...the absolute performance difference between the two replications of each condition ...was calculated for each subject. For each dependent variable the difference values were then averaged across the various time-sharing conditions and across subjects. The average differences resulting from each of the tasks became the normalization factor by which the single-dual task performance decrements were divided)." (p. 220).

By using these "normalized" scores (though these scores do not have the same characteristics as z-scores), the investigators then combined the dual task components (by determining the mean decrement score for each pair of tasks in each combination) and arrived at scores for the nine variables which represented the time-sharing efficiency of all of the dual-task pairings; where TT, CC, and LL combinations were represented by the single decrement scores only.

This set of nine dual-task variables was used as input for another factor analysis procedure. Wickens, et. al. presented both two-factor and three-factor solutions in their 1979 paper, but favored the two-factor solution as being the most appropriate. The reported final factor structures were subjected to oblique simple-structure rotations, although the correlations of factors were not presented, making it impossible for the reader to reconstruct the factor pattern or the factor structure.

The result of that factor analysis is indeterminate as far as conclusions about the time-sharing ability are concerned. The main problem becomes apparent when the correlations between the single tasks and the decrement scores are examined. (The data collected by Wickens, et. al. indicate that single task-dual task component decrement scores are non-trivially negatively correlated -- mostly around $r = -.40$ to $-.50$.) This point indicates that the method of adjusting subjects' dual-task scores was not sufficient to effectively "partial out" the influence of the subjects' initial ability levels. As a consequence, the factor structure underlying the decrement scores can not be distinquished from variance attributable to single task performance; a crucial requisite for the evaluation of the time-sharing ability. If the single task scores were included in this analysis, they could be used as "marker variables" in order to properly assess the nature of the underlying factor structure.

In conclusion, though the investigators believed that the analyses failed to show a time-sharing ability or factor; the issue was not critically evaluated with the designs appropriate to the question. Based

on this inadequate assessment, and the belief that the data under consideration represent a reasonable sample of tasks and other characteristics, a detailed reanalysis was required for an objective evalution of the data with respect to a T/S ability. Several different ways of approaching the data were considered, and many aspects of the data were discussed. Finally, post hoc interpretations were utilized in the evaluation of different models, with respect to the overall question of the existence of the time-sharing ability.

A general advisory note should be made before the reanalysis of these data is presented. Since refined measures (i.e., high reliability), replicated results, and a priori known relationships between task variables were not available, and also since the analysis is limited by the preliminary stage of model development, the rigors of maximum likelihood confirmatory factor analysis were not confronted (see discussion of LISREL, etc.). Instead, frequent use was made of less restrictive, and admittedly subjective methods of Procrustean factor rotations in the interest of gaining insight, rather than testing the adequacy, of this limited data set.

In the first stage of the reanalysis, we considered the raw scores only. (For table references, each task abbreviation is followed by its variable number.) The raw scores include all of the single tasks- T-1, C-6, L-11, and A-16; the single tasks paired with themselves- TT-2, CC-8, and LL-14 (recall that the AA combination was not used in the experiment); and the single-task components within the other dual-task combinations- T(C)-3, T(L)-4, T(A)-5, C(T)-7, C(L)-9, C(A)-10, L(T)-12, L(C)-13, L(A)-15, A(T)-17, A(C)-18, and A(L)-19. In keeping with the model discussed in the simulation presented earlier, a factor structure was considered such that twenty-five percent of the common variance of performance in dual-tasks was attributable to the T/S ability and the remaining common variance to the component tasks.

As mentioned above, the substantial correlation between the C and the L tasks gave rise to the expectation that those two tasks together defined a single underlying factor of individual differences. The A task, the T task, and the hypothetical T/S ability were each expected to define one factor each; thus suggesting that a four factor representation would likely be appropriate to reveal the structure of interest. The correlation matrix of these measures was used as input for the common factor analysis procedure (see Table 9). Given the small number of subjects, and the magnitude of the influence of the hypothetical time-sharing factor; the results of a Parallel Analysis (Montanelli & Humphreys, 1975) were not suprising -- i.e., a three factor solution was recommended. However, the fact that including the fourth factor accounted for an additional 3.8 percent of the total variance of the correlation matrix entries (determined from the eigenvalues) was not surprising to the present authors. Based on the earlier simulation, it was determined that the influence of this fourth factor was similar to the amount that would be expected if the time-sharing ability did exist in the form represented by the model.

Given the a priori expectations of the inappropriate nature of either orthogonal or oblique "simple-structure", no such simple-structure seeking

rotational procedure was implemented. In order to investigate the amount of congruence between a most advantageously rotated factor matrix and the model factor structure, an Orthogonal Procrustes procedure was used. The model target matrix is presented in Table 10. Note the similarity of this matrix with the model used in the simultion (Table 1). The only difference regards the consolidation of the two single-task ability factors (C and L). The input factor matrix (i.e., the unrotated solution) is presented in Table 11 and the closest rotation (with respect to least squares deviations) of the factor matrix is presented in Table 12. For ease of interpretation, the pairwise plots of factor loadings are presented in Figures 2A through 2F.

In evaluating the results of the rotational procedure, it is important to note both the similarities and the discrepancies between the rotated factor matrix and the target factor structure. For the most part, the solution is suggestive of some T/S factor, along with the separate ability factors determined by using the single tasks as defining "marker variables". However, even though most of the residuals (i.e., the differences in loadings between the target and rotated factor matrix -- see Table 13) are smaller than 0.1, the single Tracking task obviously violates the separation between the single and dual-task loadings on the T/S ability factor. On the other hand, all of the loadings of the dual-tasks on the T/S factor are positive; and many approach the .5 maximal loading specified by the model. The fact that the single tasks have non-zero positive loadings on the T/S factor may also be indicative of some communality between all of these abilities; in other words, some "g" factor.

To compare the raw (i.e., not the decrement) score analysis to an analysis where individual asymmetric trade-off strategies were balanced out;the raw dual-task component scores (in z-score form) were averaged for each subject. This analysis used the single-task scores as "marker" variables, just as before, but each dual-task combination was included as a single variable (See reference note 3). The resulting thirteen variables were as follows: 1) T, 2) TT, 3) TC, 4) TL, 5) TA, 6) C, 7) CC, 8) CL, 9) CA, 10) L, 11) LL, 12) LA, and 13) A. Note that the tasks paired with themselves also represented the average raw scores for each subject. (In other words, since the measures of such tasks were each on the same scale, the scores could be averaged without introducing confounding influences from mean and variance values. This procedure could not be used for raw scores across the other task combinations, since different dependent variables were used.) The correlation matrix is shown in Table 14.

The model in this situation, was derived from the hypothetical model discussed before -- where the time-sharing ability accounts for twenty-five percent of the common variance of the dual-task variables and the component abilities account for equal proportions of the remaining seventy-five percent of the common variance. The model factor matrix is presented in Table 15. The results of the factor analysis of these data are presented in Tables 16 and 17.

As the Parallel Analysis of the data reveals, the existence of an underlying fourth factor is questionable, but since the a priori expectations have mostly circumvented determination of the number of

factors; this point should only be taken as possibly suggestive of an over-capitalization on chance in a Procrustes procedure using four factors. The results from the Procrustes rotation to the model are presented in Table 18, as well as Figures 3A to 3F (the residuals from comparing the model and the rotation are shown in Table 19). The magnitudes of the residuals indicate that the closest rotation to the model in this case, does not differ substantially overall from the solution with the component task raw scores (though this is a qualitative and not a quantitative statement).

Since Wickens, et. al. presented evidence in which they made use of difference scores, a decision was made to further investigate this type of data. However, at the outset it is clear that the complex nature of difference scores may preclude inferential use of such data in this topic area. (Future analyses should consider extensive use of of covariance adjustment techniques as they are generally superior to difference scores; see Feldt, 1958; Keppel, 1973). While difference scores are themselves complex entities, joint scores based on a normalization procedure are even further removed from the raw data, and depend on specific assumptions about dual task performance. Based on this foundation, a step by step analysis was taken with respect to these scoring methods and their respective ramifications.

First of all, it should be reiterated that the single-to-dual task raw scores were nearly all highly correlated (see Table 9) and those correlations often approached the magnitudes of the respective single task reliabilities. The initial interpretation based on those correlations is that, in general, subjects that rank high in the sample distribution for single tasks also rank high on the tasks when they are performed in conjunction with simultaneous performance of an additional task. (This point is additional evidence in favor of our allocation of variance components in the model of T/S.) When each sub hc;as component task scores in the dual-task situation are subtracted from their respective single task baseline performance level, the relationship is quite different between the single task baseline and the newly created difference scores.

With the exception of two of the Tracking score variables, and one of the Classification scores, all of the single-to-dual difference scores are moderately to highly negatively correlated (see Table 20). Based on these data, along with the raw score correlations, the interpretation of these relationships is that those subjects who do poorly in single task performance (with respect to the rest of the sample) show much smaller decrements in performance than the subjects who perform well. However, the extent of the good subjects' decrements are not so large in magnitude to indicate a change in the subjects' respective positions in the single and dual-task score distributions! (More colloquially, one might say that "the higher they are, the harder they fall; but the lower ones still land a bit lower.") Such a result is suggestive of a situation where single task scores will show more variability than dual task scores.

While a cursory inspection of these intercorrelations shows this general relationship between the single task performance levels and the difference scores, a more exact statement may be made via the use of factor

analysis. Recall that this type of analysis is useful in actually finding the fewest number of factors that give an adequate fit to the data. The results of such an analysis on the correlations between single-task scores and dual-task difference scores are presented in Tables 21 and 22. Two points are to be made from this analysis. The latent root series indicates that these data have complex structure (i.e., many factors are necessary for accounting for a suitable amount of variance); in fact, this structure is much more complex than the raw scores data shown earlier (see Tables 11 and 12). To estimate the actual number of latent "factors" a Parallel Analysis was performed. The results indicated that approximately six factors were underlying the set of variables under discussion. One basic interpretation is that there are poosibly complex, non linear functions relating raw single task scores and dual-task difference scores.

The second point can be seen from an examination of the first principal factor (which accounts for about 30 percent of the total variance) presented in Table 22. In effect, this factor shows the pervasive powerful negative relationship between the single task raw scores and the derived dual-task difference scores. A likely interpretation of this component is that it represents the general relationship between these variables and the overall performance levels of the subjects. In other words, the single tasks (especially the Classification and Line Judgment tasks) are most highly related to the subjects' general ability (in this set of tasks), and the dual tasks (especially the C and L combinations) are most highly negatively correlated with overall ability (i.e., raw scores).

In addition to the analysis of the raw single task scores and the dual-task component difference scores, a similar analysis was performed on the raw single tasks with the combined dual-task difference scores (i.e. the mean difference scores based on the average of the z-transformed component scores). Since the results were, for all intents and purposes, identical in overall structure with the raw difference scores, the tables and figures are not presented. The conclusion from these analyses is that the possibility of differences in trade-off asymmetries between subjects does not influence the relationship between difference scores and the raw single task scores. Therefore, it can be inferred from the data that while single and dual-task component scores are highly correlated, a substantial relationship exists between the amount of resulting decrement in performance and the initial level of subjects' ability. Indeed, such may be the major pervasive source of individual differences in complex task performance.

The final conclusion about the hypothetical T/S ability from the data collected by Wickens et. al. is that there is a reasonable possibility of some underlying T/S trait that transcends the different task combinations. Certainly more of this type of research needs to be completed with reference to this issue.

Conclusion

In this report, a large number of methodological, design, and analysis issues have been discussed. Several findings from the psychometric literature have been presented as they have related to the inferences made

possible from data analysis; especially with respect to the use of dual-task correlational studies of individual differences. In addition, a review of four relatively recent studies has revealed that by taking these methodological and analysis issues into account, serious doubts arise as to the utility of analyses and conclusions reported by the respective authors.

We carried out a detailed reanalysis of the Wickens, et. al. single and dual-task data. The analysis showed that several problems inherent in all of these studies have prevented a crucial test of the existence of the T/S ability (in the sense of a strictly confirmatory analysis). The three major problems were 1) number of subjects, 2) selection of variables, and 3) refined understanding of the processes involved in single tasks and the interrelations between such tasks -- which prevent the derivation of models adequate to rigorous testing.

The research literature shows that the amount of useful information resulting from the use of factor analytic methods is strongly related to the amount of a priori specificity about theory and data that is brought to the experiment and analysis. The social science literature abounds with studies that support the "garbage in -- garbage out" maxim where factor analysis is concerned. Armstrong (1967) in a very powerful empirical demonstration from the physical science domain, suggests six specific considerations that are crucial for intelligent use of factor analysis.

He proposes that the potential user of factor analysis "should make prior evaluations of such things as: "a) the nature of the relationships between the variables of interest -- i.e., whether transformations and linear relationships are appropriate to the data; b) the number of underlying factors of importance; c) "types of factors" that underlie the data, i.e. whether simple structure is an appropriate representation of the solution, or whether complex factors are useful; d) which particular variables are to be considered, whether they are "logically consistent with the theory", and so on; e) whether the factors themselves are to be related to one another; i.e. orthogonal or oblique structures; and f) "what ..the most meaningful communality estimates [are] for the problem. (The choice here will influence the number of factors" determination.)

The problems resulting from use of small samples of subjects (especially when they come from restricted populations -- e.g., college students -- and cognitive abilities are under consideration), involve both broad sampling distributions of correlations as well as stability and mathematical limitations on multivariate data analysis procedures such as factor analysis. As stated before, the number of subjects in a study which will be analyzed in this manner should be several times the number of variables under consideration. If this requirement is not fulfilled, little possibility exists for confidence in any determined structure underlying the data; just as the confidence interval for any given correlation broadens under the same circumstances. Recall the rules of thumb of three variables to determine each factor and about a minimum of about ten subjects per variable measured.

The selection of variables for use in this type of dual-task study should require that the investigators seriously consider not only task

facets such as ceiling, floor, and magnitude of variability issues, but also practice effects and time to stabilization of individual performance, as well as the final reliability of the scoring methods used for assessment of performance. In addition to these single task issues, the interrelationship between the variables in dual-task situations is also important to determination or evaluation of the existence of a trans-situational time-sharing ability. When single tasks correlate moderately or highly, the variance components of the dual-tasks will be more difficult to cleanly separate from the single task abilities. This problem was of primary importance in the Hawkins, Rodriguez, and Reicher (1979) paper. Also, these interrelationships were the cause of the overdetermination of one factor and the underdetermination of residual variance components in the Wickens, et. al. (1979, 1981) study.

In this paper, a very simple hypothetical model representing the time-sharing ability was adopted. The use of this model in the reanalysis of the other studies showed that it is clearly lacking in the representation of the structural characteristics underlying the data. On the other hand, it was successful in many cases in providing insight into aspects of the data which could not be derived with the use of "simple-structure" seeking factor rotation procedures. Use of this simple model provided what could be interpreted as tentative evidence for some trans-situational time-sharing factor; "tentative" -- since only a few different tasks were extensively considered on small samples. However, to go beyond the tentative nature of this claim, it is necessary for investigators to decide how different variables affect the distribution of individuals on performance measures. In addition, if such considerations as asymmetric trade-off strategies or other relevant theoretical issues are determined to be related to individual differences in performance; then adjustments to the model must be made at the level of each experiment. Crucial tests of the T/S ability will need to be based on explicit models and confirmatory factor analytic techniques. More research is needed that addresses these particular topics involved in the fine tuning of models of time-sharing behavior before such a junction is reached.

Reference Notes

Note 1: The necessity of examining the interrelations between several dual-task combination performance distributions, with the influence of the component task abilities removed from each dual-task score, makes the use of second and higher order partial correlations appropriate to the analytic scheme, as well as factor analysis. Unfortunately, interpretation of second and higher order partial correlation coefficients is often found to be problematic (Ferguson, 1976). In addition, factor analytic techniques will allow the inclusion of component task variables into an analysis of dual-task scores, allowing for both separation of the respective amounts of common variance to the underlying abilities, and integration of single and dual-task variables into a unified theoretical model of individual differences. As such, the factor analytic approach is superior to the sole use of partial correlations.

Note 2: While principal components analysis is often used as a "first stage" of factor analytic procedures (see Tatsuoka, 1971; Harmon, 1976); it is by no means equivalent in either derived structure or inferential properties. From a practical point of view, the major difference between principal components analysis and factor analysis regards the diagonal elements of the input correlation matrix -- principal components methods use unities (i.e., ones) in the diagonal, and factor analysis requires estimates of communalities in the diagonal.

As such, a principal components analysis will result in a solution which is of mathematical interest, i.e., "each component, in turn makes a maximum contribution to the sum of the variances of the n variables" (Harmon, p. 17). Factor analysis, on the other hand, involves the separation of common factors, unique (or specific) factors (and when desired, error factors). The nature of these factors is that of hypothetical entities determined with fallible data. The factor analytic model is designed to "maximally reproduce the correlations" which were used as input. In general, the principal components model is not adequate for inferential purposes when using fallible data, in that it allows for no distinction between common variance, unique variance, etc.; which are certain to be present in empirical data.

Note 3: A difference exists between the method of determining joint (or cross-) decrement scores used by Wickens, et. al. and that used in the present data reanalysis performed here. The method used by the previous authors determined the proportional influence of the component difference scores by dividing the scores by a value that represented a mean within-subject variability (from replication to replication) measure for each respective component. In the present reanalysis, between-subject variabilities (i.e., the actual standard deviations of scores) for each component were computed and used for "normalization", so that the joint decrement scores represent mean values of z-scores on the component difference measures. This method appears to be more appropriate, since the topic under consideration is related to interindividual differences, rather than intraindividual differences. In practice, the resulting differences between these two methods are not generally known. For these data, though, the respective correlations differed only to a small, rather trivial degree.

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TABLE 1: FACTOR MODEL -- FOUR TASK FACTORS WITH TIME-SHARING FACTOR

VARIABLE		FACTOR "A"	"B"	"C"	"D"	"T/S"
1	A	1.000	.000	.000	.000	.000
2	AA	.866	.000	.000	.000	.500
3	AB	.612	.612	.000	.000	.500
4	AC	.612	.000	.612	.000	.500
5	AD	.612	.000	.000	.612	.500
6	B	.000	1.000	.000	.000	.000
7	BB	.000	.866	.000	.000	.500
8	BC	.000	.612	.612	.000	.500
9	BD	.000	.612	.000	.612	.500
10	C	.000	.000	1.000	.000	.000
11	CC	.000	.000	.866	.000	.500
12	CD	.000	.000	.612	.612	.500
13	D	.000	.000	.000	1.000	.500
14	DD	.000	.000	.000	.866	.000

TABLE 2: RECONSTRUCTED MODEL CORRELATION MATRIX

		A	AA	AB	AC	AD	B	BB
1	A	1.000						
2	AA	.866	1.000					
3	AB	.612	.780	1.000				
4	AC	.612	.780	.625	1.000			
5	AD	.612	.780	.625	.625	1.000		
6	B	.000	.000	.612	.000	.000	1.000	
7	BB	.000	.250	.780	.250	.250	.866	1.000
8	BC	.000	.250	.625	.625	.250	.612	.780
9	BD	.000	.250	.625	.250	.625	.612	.780
10	C	.000	.000	.000	.612	.000	.000	.000
11	CC	.000	.250	.250	.780	.250	.000	.250
12	CD	.000	.250	.250	.625	.625	.000	.250
13	D	.000	.000	.000	.000	.612	.000	.000
14	DD	.000	.250	.250	.250	.780	.000	.250

		BC	BD	C	CC	CD	D	DD
8	BC	1.000						
9	BD	.625	1.000					
10	C	.612	.000	1.000				
11	CC	.780	.250	.866	1.000			
12	CD	.625	.625	.612	.780	1.000		
13	D	.000	.612	.000	.000	.612	1.000	
14	DD	.250	.780	.000	.250	.780	.866	1.000

TABLE 3: LATENT ROOT PARALLEL ANALYSIS -- HYPOTHETICAL MODEL

EIGENVALUES

	REAL DATA	RANDOM DATA*	DIFFERENCE
1	6.055	.054	6.011
2	2.500	.040	2.460
3	2.500	.032	2.468
4	2.500	.025	2.475
5	.445	.019	.426
6	.000	.013	-.013
7	.000	.003	-.003
8	.000		
9	.000		
10	.000		
11	.000		
12	.000		
13	.000		
14	.000		

*RANDOM DATA WERE GENERATED BY A PROGRAM WRITTEN BY LEDYARD TUCKER APPROXIMATING CONDITIONS SPECIFIED IN MONTANELLI AND HUMPHREYS (1976).

TABLE 4: FACTOR MATRIX -- PRINCIPAL FACTORS

VARIABLE		FACTOR				
		I	II	III	IV	V
1	A	.398	-.757	.270	.322	.303
2	AA	.647	-.656	.234	.279	-.136
3	AB	.790	-.119	.569	.194	-.027
4	AC	.790	-.273	-.227	.499	-.027
5	AD	.790	-.535	-.011	-.298	-.027
6	B	.398	.562	.658	-.006	.303
7	BB	.647	.487	.570	-.005	-.136
8	BC	.790	.535	.011	.278	-.027
9	BD	.790	.273	.227	-.499	-.027
10	C	.398	.311	-.641	.492	.303
11	CC	.647	.270	-.555	.426	-.136
12	CD	.790	.119	-.569	-.194	-.027
13	D	.398	-.117	-.287	-.808	.303
14	DD	.647	-.101	-.249	-.700	-.136

TABLE 5: FACTOR MATRIX -- VARIMAX ROTATION

VARIABLE		FACTOR I	II	III	IV	V
1	A	-.037	.963	-.038	-.037	-.262
2	AA	.099	.965	.099	.099	.200
3	AB	.698	.698	.086	.086	.106
4	AC	.085	.698	.698	.086	.106
5	AD	.085	.698	.085	.698	.106
6	B	.963	-.037	-.037	-.037	-.261
7	BB	.965	.099	.099	.099	.200
8	BC	.698	.086	.698	.086	.106
9	BD	.698	.086	.085	.698	.106
10	C	-.037	-.037	.963	-.037	-.261
11	CC	.099	.099	.965	.099	.200
12	CD	.086	.085	.698	.698	.106
13	D	-.037	-.037	-.037	.963	-.261
14	DD	.099	.099	.099	.965	.200

TABLE 6: HAWKINS, ET. AL. DATA -- LATENT ROOT PARALLEL ANALYSIS

EIGENVALUES

	REAL DATA	RANDOM DATA	DIFFERENCE
1	4.750	1.584	3.166
2	.770	1.067	-.297
3	.468	.743	-.275
4	.218	.424	-.206
5	.127		
6	-.044		
7	-.100		
8	-.153		

TABLE 7: WICKENS, ET. AL. SINGLE TASK INTERCORRELATIONS

	TRACKING	CLASSIFICATION	LINE JUDGEMENT
CLASSIFICATION	.21		
LINE JUDGEMENT	-.09	.63	
AUDITORY	.37	.42	.19

TABLE 8
SINGLE-DUAL TASK FACTOR PATTERN MATRIX

	(a) TWO-FACTOR SOLUTION		(b) THREE-FACTOR SOLUTION		
VARIABLE	FACTOR 1	FACTOR 2	FACTOR 1	FACTOR 2	FACTOR 3
S Track	-0.03	0.95*	0.02	0.90	0.08
D Track	0.02	0.84*	-0.03	0.95*	-0.09
S Class	0.82*	-0.02	0.73*	-0.07	-0.14
D Class	0.98*	-0.06	0.79*	-0.07	-0.29
S Lines	0.79*	0.31	0.90*	0.13	0.14
D Lines	0.87*	0.01	0.87*	-0.10	-0.01
S Aud	-0.42*	0.32	0.03	0.02	0.80*
D Aud	-0.04	0.25	-0.10	-0.03	0.80*

*$p < 0.01$

TABLE 9: RAW DATA INTERCORRELATIONS: WICKENS, ET. AL. DATA*

	T	TT	T(C)	T(L)	T(A)	C	C(T)	CC	C(L)
TT	.650								
T(C)	.839	.639							
T(L)	.706	.655	.848						
T(A)	.912	.705	.920	.860					
C	.209	.135	.122	.146	.235				
C(T)	.260	.311	.118	.016	.239	.775			
CC	.204	.262	.122	.132	.271	.845	.773		
C(L)	.310	.276	.115	.114	.300	.721	.712	.758	
C(A)	.186	.244	.108	.154	.200	.791	.696	.802	.675
L	-.091	.083	-.203	-.106	-.067	.635	.600	.592	.574
L(T)	.230	.201	.019	-.091	.144	.559	.769	.613	.780
L(C)	.297	.277	.213	.237	.364	.670	.636	.827	.699
LL	.229	.366	.188	.255	.338	.543	.589	.720	.779
L(A)	.049	.232	-.050	.095	.094	.593	.524	.654	.597
A	.371	.213	.283	.120	.319	.423	.519	.434	.287
A(T)	.315	.247	.138	.140	.273	.478	.568	.637	.497
A(C)	.276	.241	.154	.123	.250	.392	.519	.537	.417
A(L)	.296	.152	.108	.087	.231	.401	.568	.493	.497

	C(A)	L	L(T)	L(C)	LL	L(A)	A	A(T)	A(C)
L	.621								
L(T)	.641	.644							
L(C)	.679	.559	.610						
LL	.604	.542	.649	.780					
L(A)	.782	.781	.701	.676	.611				
A	.515	.193	.291	.309	.226	.196			
A(T)	.595	.278	.425	.531	.488	.460	.696		
A(C)	.611	.206	.412	.431	.350	.429	.659	.827	
A(L)	.550	.227	.523	.485	.444	.426	.544	.805	.878

*NOTE THAT THE RAW SCORES HAVE BEEN ALTERED SO THAT LARGER SCORES INDICATE BETTER PERFORMANCE FOR ALL VARIABLES.

TABLE 10: FACTOR MODEL FOR WICKENS, ET. AL. DATA

VARIABLE		FACTOR			
		"T"	"C & L"	"A"	"T/S"
1	T	1.000	.000	.000	.000
2	TT	.860	.000	.000	.500
10	C(A)	.000	.860	.000	.500
11	L	.000	1.000	.000	.000
12	L(T)	.000	.860	.000	.500
13	L(C)	.000	.860	.000	.500
14	LL	.000	.860	.000	.500
15	L(A)	.000	.860	.000	.500
16	A	.000	.000	1.000	.000
17	A(T)	.000	.000	.860	.500
18	A(C)	.000	.000	.860	.500
19	A(L)	.000	.000	.860	.500

TABLE 11: WICKENS, ET. AL. DATA FACTOR MATRIX -- PRINCIPAL FACTORS

VARIABLE		FACTOR			
		I	II	III	IV
1	T	.446	.794	-.009	-.016
2	TT	.427	.608	.167	.145
3	T(C)	.304	.890	.034	-.087
4	T(L)	.296	.826	.199	.048
5	T(A)	.466	.856	.113	-.013
6	C	.797	-.190	.162	-.441
7	C(T)	.834	-.174	-.003	-.222
8	CC	.878	-.177	.095	-.189
9	C(L)	.822	-.141	.217	.047
10	C(A)	.853	-.197	.004	-.110
11	L	.614	-.460	.344	-.008
12	L(T)	.765	-.283	.167	.193
13	L(C)	.823	-.063	.191	.059
14	LL	.770	-.059	.279	.222
15	L(A)	.739	-.313	.246	.266
16	A	.568	.122	-.521	-.292
17	A(T)	.746	-.007	-.514	.074
18	A(C)	.686	.007	-.624	.144
19	A(L)	.695	-.043	-.552	.250

TABLE 12: WICKENS ET. AL. DATA -- PROCRUSTES ROTATION

VARIABLE		FACTOR		
	"T"	"C & L"	"A"	"T/S"
1 T	.808	.025	.166	.383
2 TT	.615	.087	-.044	.461
3 T(C)	.908	-.052	.056	.261
4 T(L)	.825	-.043	-.088	.349
5 T(A)	.890	.061	.062	.403
6 C	.165	.899	.233	.039
7 C(T)	.082	.772	.335	.247
8 CC	.096	.830	.251	.293
9 C(L)	.060	.729	.058	.455
10 C(A)	.030	.753	.303	.343
11 L	-.226	.769	-.112	.229
12 L(T)	-.136	.665	.043	.518
13 L(C)	.121	.684	.079	.482
14 LL	.076	.613	-.062	.581
15 L(A)	-.179	.659	-.056	.554
16 A	.225	.288	.739	.122
17 A(T)	.022	.329	.689	.493
18 A(C)	-.020	.208	.749	.525
19 A(L)	-.086	.221	.658	.603

TABLE 13: RESIDUAL MATRIX

VARIABLE		RESIDUALS		
	"T"	"C & L"	"A"	b/S
1 T	.191	-.025	-.166	-.383
2 TT	.244	-.087	.044	.038
3 T(C)	-.048	.052	-.056	.238
4 T(L)	.034	.043	.088	.150
5 T(A)	-.030	-.061	-.062	.096
6 C	-.165	.100	-.233	-.039
7 C(T)	-.082	.087	-.335	.252
8 CC	-.096	.029	-.251	.206
9 C(L)	-.060	.130	-.058	-.044
10 C(A)	-.030	.106	-.303	.156
11 L	.226	.230	.112	-.229
12 L(T)	.136	.194	-.043	-.018
13 L(C)	-.121	.175	-.079	.017
14 LL	-.076	.246	.062	-.081
15 L(A)	.179	.200	.056	-.054
16 A	-.225	-.228	.260	-.122
17 A(T)	-.022	-.329	.170	.006
18 A(C)	.020	-.208	.110	-.025
19 A(L)	.086	-.221	.201	-.103

TABLE 14: SINGLE TASK SCORE AND JOINT DUAL-TASK SCORE INTERCORRELATIONS

TT	.650											
TC	.735	.635										
TL	.694	.635	.820									
TA	.769	.597	.782	.729								
C	.209	.135	.600	.523	.447							
CC	.204	.262	.599	.552	.569	.845						
CL	.329	.300	.608	.701	.592	.755	.860					
CA	.258	.271	.551	.550	.654	.659	.746	.666				
L	-.091	.083	.265	.414	.132	.635	.592	.615	.461			
LL	.229	.336	.520	.670	.518	.543	.720	.846	.531	.542		
LA	.204	.227	.456	.618	.590	.588	.679	.724	.871	.597	.624	
A	.371	.213	.536	.305	.636	.423	.434	.323	.654	.193	.226	.435
	T	TT	TC	TL	TA	C	CC	CL	CA	L	LL	LA

TABLE 15: FACTOR MODEL FOR WICKENS, ET. AL. DATA

VARIABLE		FACTOR "T"	"C & L"	"A"	"T/S"
1	T	1.000	.000	.000	.000
2	TT	.866	.000	.000	.500
3	TC	.612	.612	.000	.500
4	TL	.612	.612	.000	.500
5	TA	.612	.000	.612	.500
6	C	.000	1.000	.000	.000
7	CC	.000	.866	.000	.000
8	CL	.000	.866	.000	.500
9	CA	.000	.612	.612	.500
10	L	.000	1.000	.000	.000
11	LL	.000	.866	.000	.500
12	LA	.000	.612	.612	.500
13	A	.000	.000	1.000	.000

TABLE 16: WICKENS, ET. AL. DATA -- SQUARED MULTIPLE CORRELATIONS

VARIABLE		R^2
1	T	.863
2	TT	.633
3	TC	.865
4	TL	.892
5	TA	.895
6	C	.834
7	CC	.896
8	CL	.896
9	CA	.901
10	L	.723
11	LL	.809
12	LA	.896
13	A	.733

TABLE 17: PARALLEL ANALYSIS OF WICKENS, ET. AL. DATA

EIGENVALUES

	REAL DATA	RANDOM DATA	DIFFERENCE
1	7.196	1.422	5.774
2	2.008	1.079	.928
3	.905	.860	.045
4	.466	.686	-.220
5	.287	.524	-.238
6	.148	.349	-.200
7	.115		
8	.038		
9	-.021		
10	-.045		
11	-.067		
12	-.076		
13	-.116		

TABLE 18: PROCRUSTES ROTATION OF WICKENS, ET. AL. DATA

VARIABLE		FACTOR			
		"T"	"C & L"	"A"	"T/S"
1	T	.866	.053	.164	.278
2	TT	.644	.099	.005	.402
3	TC	.713	.501	.230	.245
4	TL	.556	.482	.007	.589
5	TA	.618	.315	.466	.440
6	C	.112	.884	.223	.015
7	CC	.100	.875	.231	.205
8	CL	.149	.824	.047	.424
9	CA	.022	.557	.640	.431
10	L	-.221	.716	-.025	.252
11	LL	.113	.672	-.078	.525
12	LA	-.103	.549	.411	.647
13	A	.266	.289	.740	.047

TABLE 19: RESIDUAL MATRIX (MODEL - ROTATION = RESIDUAL)

VARIABLE		RESIDUALS			
		"T"	"C & L"	"A"	"T/S"
1.	T	.134	-.053	-.164	-.278
2.	TT	.222	-.099	-.005	.098
3.	TC	-.101	.111	-.230	.255
4.	TL	.056	.131	-.007	-.089
5.	TA	-.006	-.315	.146	.060
6.	C	-.112	.116	-.223	-.015
7	CC	-.100	-.009	-.231	.295
8.	CL	-.149	.042	-.047	.076
9.	CA	-.218	.055	-.027	.069
10	L	.221	.284	.025	-.252
11.	LL	-.113	.194	.076	-.253
12.	LA	.103	.063	.202	-.147
13.	A	-.266	-.289	.260	-.047

TABLE 20: CORRELATION MATRIX OF SINGLE AND DUAL-TASK DIFFERENCE SCORES

	T	TT	T(C)	T(L)	T(A)	C	C(T)	CC	C(L)
TT	-.454								
T(C)	.218	.096							
T(L)	-.150	.389	.609						
T(A)	.338	.148	.709	.642					
C	.209	-.096	-.050	-.033	.174				
C(T)	.154	.195	-.134	-.391	-.068	-.009			
CC	-.117	.248	.034	-.001	.021	-.731	.245		
C(L)	-.073	.095	-.065	-.087	-.139	-.878	.175	.773	
C(A)	-.039	.241	.007	.057	-.068	-.344	.205	.512	.413
L	-.091	.208	-.248	-.044	.005	.635	.165	-.394	-.478
L(T)	.397	-.299	-.041	-.438	-.097	-.037	.472	.171	.267
L(C)	.327	-.277	.298	.049	.223	-.274	-.066	.359	.253
LL	.253	-.175	.321	.113	.230	-.412	-.031	.428	.435
L(A)	.211	.008	.144	.184	.191	-.064	-.101	.236	.112
A	.371	-.202	.029	-.254	.080	.423	.299	-.211	-.384
A(T)	-.185	.183	-.206	.183	-.033	-.084	-.091	.238	.202
A(C)	-.216	.214	-.116	.195	-.018	-.169	-.061	.254	.257
A(L)	-.197	.091	-.184	.126	-.084	-.173	-.026	.170	.282

	C(A)	L	L(T)	L(C)	LL	L(A)	A	A(T)	A(C)
L	-.036								
L(T)	.183	-.332							
L(C)	.042	-.794	.484						
LL	.094	-.847	.523	.894					
L(A)	.473	-.330	.458	.527	.459				
A	.132	.193	.142	-.005	-.086	.005			
A(T)	-.006	.025	.024	.103	.096	.283	-.656		
A(C)	.150	-.050	.089	.074	.090	.328	-.666	.821	
A(L)	.023	-.043	.153	.073	.110	.238	-.735	.844	.906

TABLE 21: LATENT ROOT PARALLEL ANALYSIS -- DIFFERENCE SCORES

	REAL DATA	RANDOM DATA	DIFFERENCE
1	4.779	1.885	2.894
2	3.436	1.562	1.875
3	2.575	1.321	1.254
4	2.009	1.135	.874
5	1.579	.977	.602
6	.855	.834	.021
7	.527	.695	-.168
8	.333	.551	-.218
9	.132	.385	-.254
10	.078		
11	.065		
12	.026		
13	-.017		
14	-.023		
15	-.034		
16	-.045		
17	-.078		
18	-.110		
19	-.115		

TABLE 22: FIRST PRINCIPAL FACTOR -- DIFFERENCE SCORES

VARIABLE		I
1	T	-.019
2	TT	.068
3	T(C)	.130
4	T(L)	.146
5	T(A)	.053
6	C	-.720
7	C(T)	.006
8	CC	.713
9	C(L)	.753
10	C(A)	.350
11	L	-.711
12	L(T)	.399
13	L(C)	.650
14	LL	.740
15	L(A)	.521
16	A	-.504
17	A(T)	.489
18	A(C)	.559
19	A(L)	.545

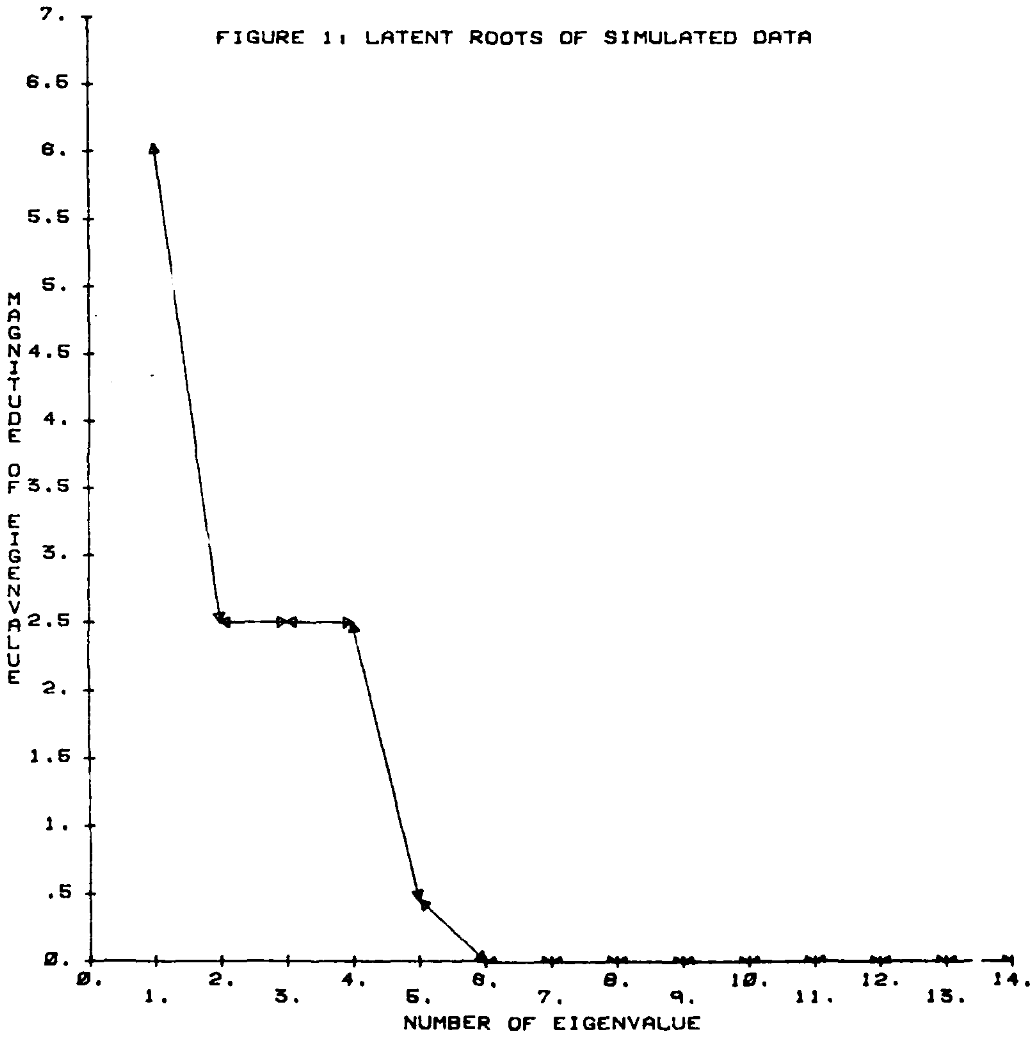
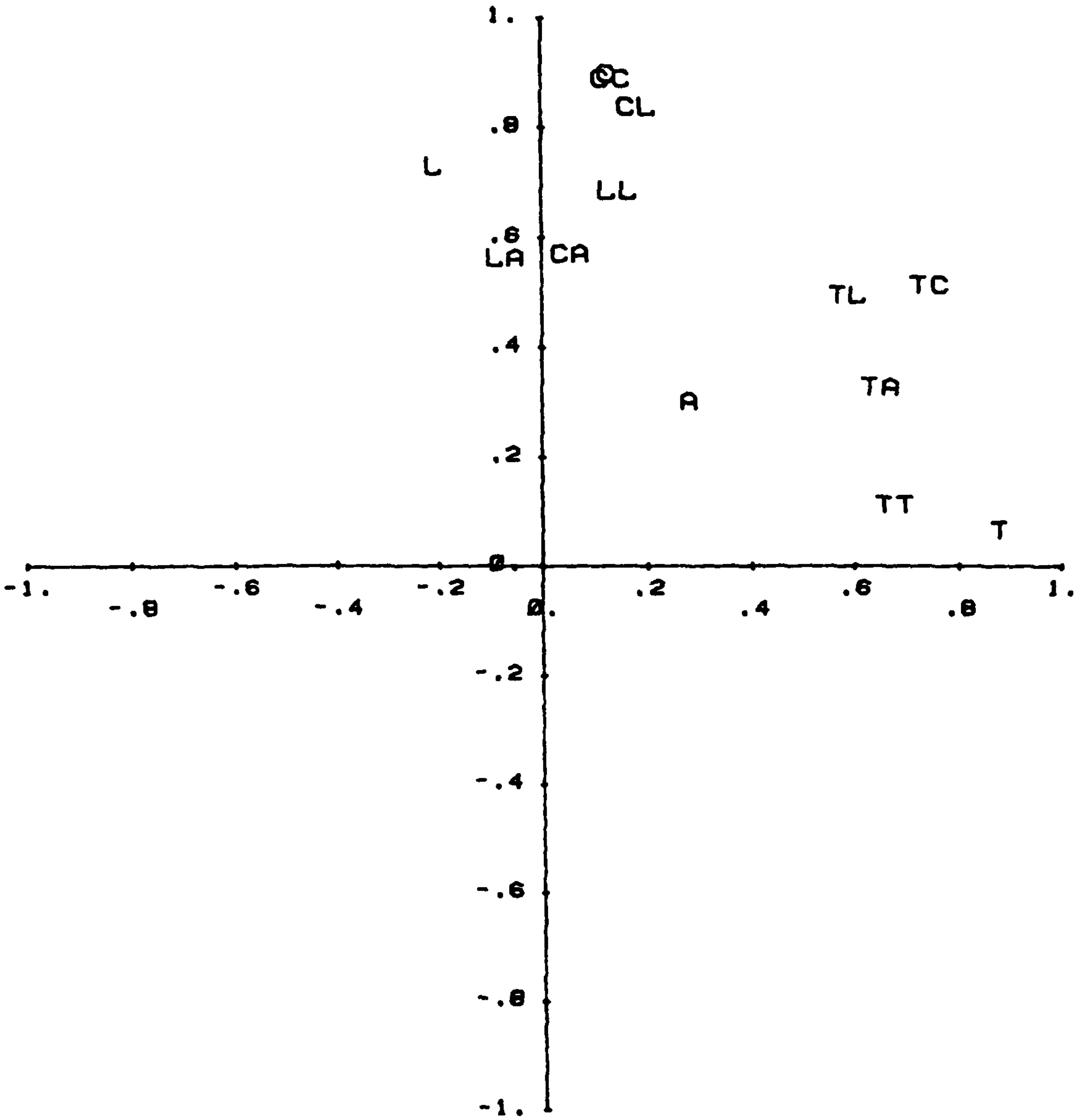


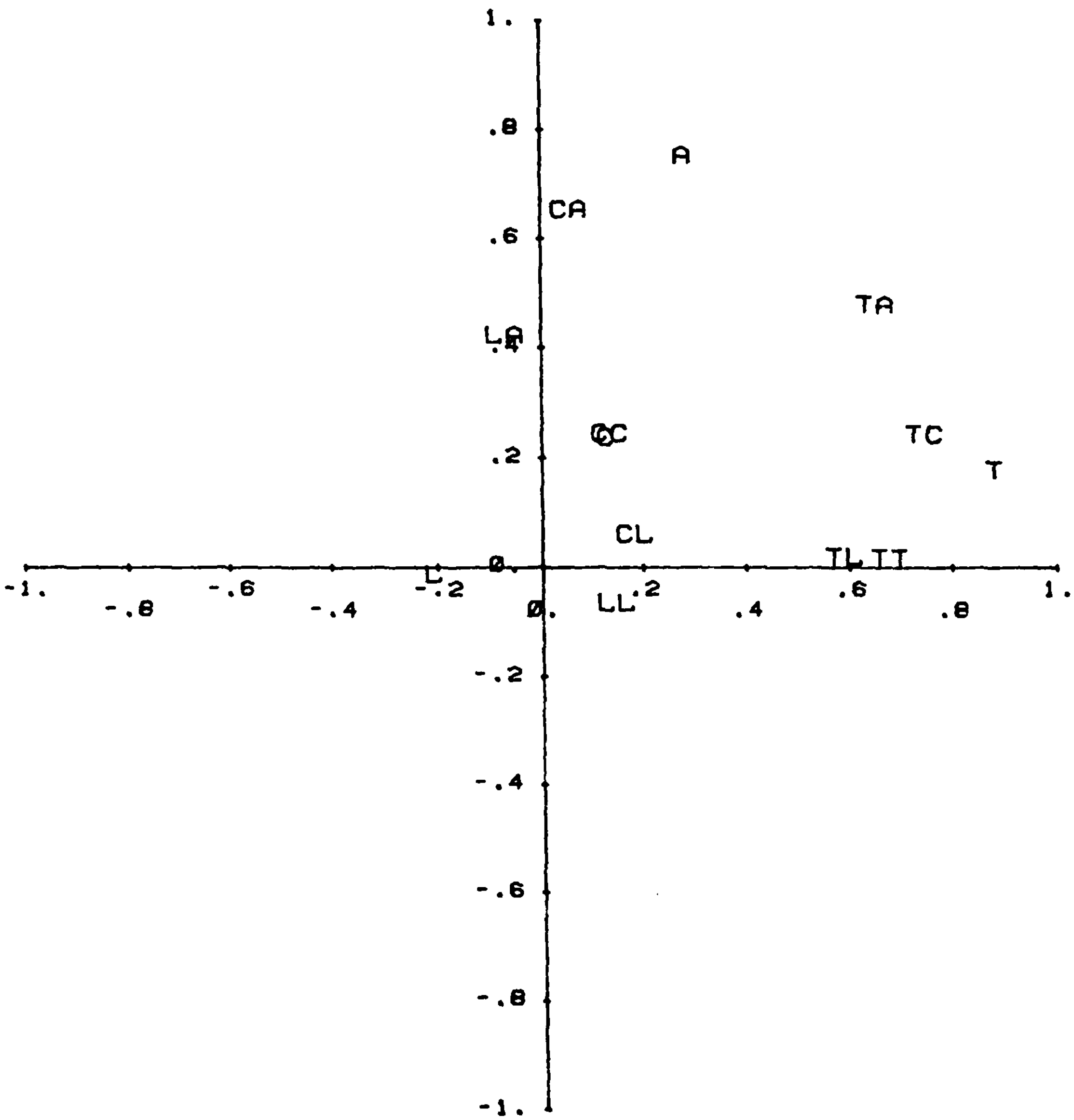
FIGURE 1: LATENT ROOTS OF SIMULATED DATA
7.
6.5
6.
5.5
5.
4.5
4.
3.5
3.
2.5
2.
1.5
1.
.5
0.
MAGNITUDE OF EIGENVALUE
0.
1.
2.
3.
4.
5.
6.
7.
8.
9.
10.
11.
12.
13.
14.
NUMBER OF EIGENVALUE

FIGURE 2A: PROCRUSTES ROTATION OF WICKENS ET. AL. DATA



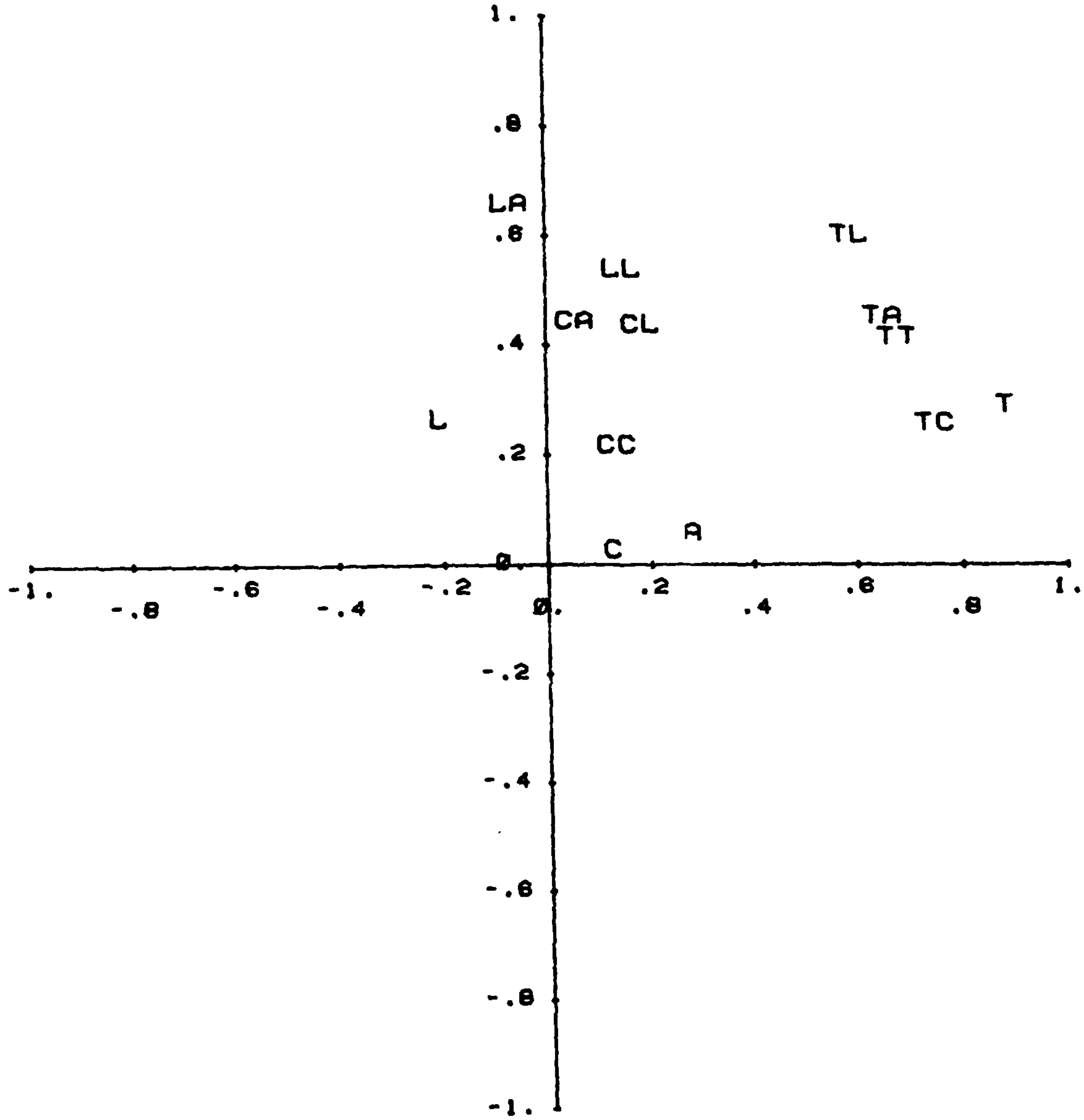
HORIZONTAL AXIS: FACTOR I -- TRACKING
VERTICAL AXIS : FACTOR II -- CLASS. AND LINE.

FIGURE 2B: PROCRUSTES ROTATION OF WICKENS ET. AL. DATA



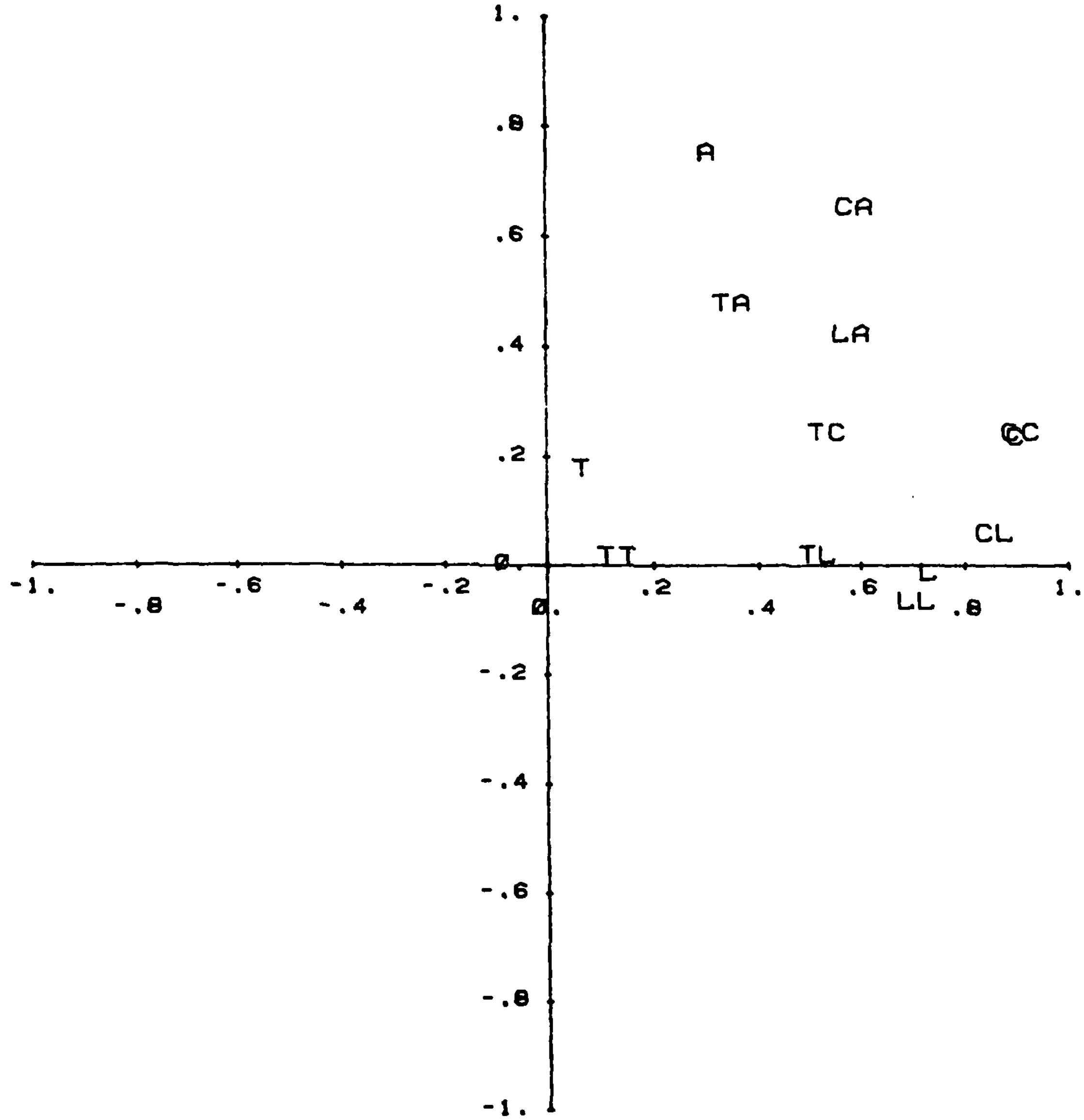
HORIZONTAL AXIS: FACTOR I -- TRACKING
VERTICAL AXIS : FACTOR III -- AUDITORY

FIGURE 2C: PROCRUSTES ROTATION OF WICKENS ET. AL. DATA



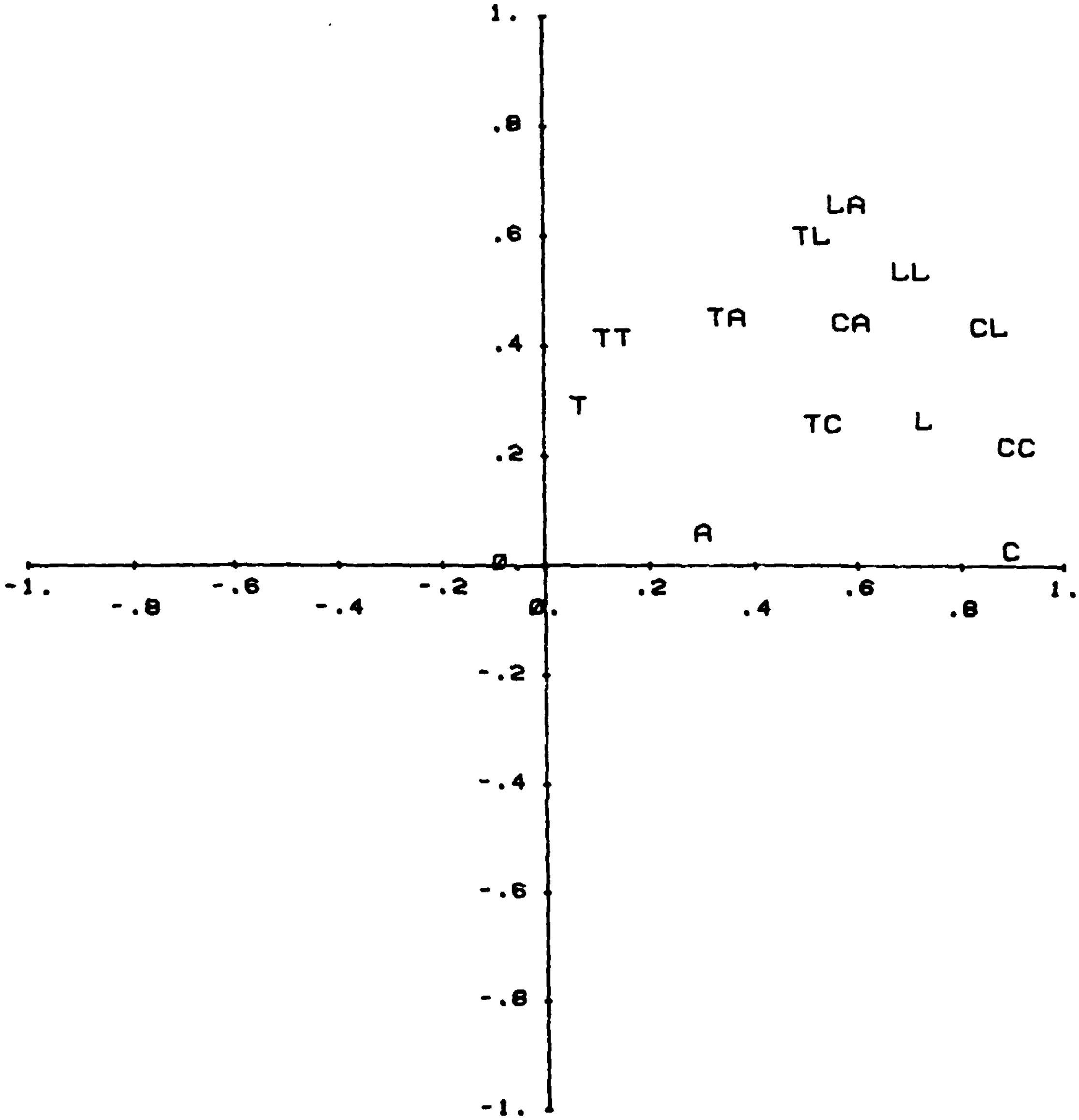
HORIZONTAL AXIS: FACTOR I -- TRACKING
VERTICAL AXIS : FACTOR IV -- TIME-SHARING

FIGURE 2D: PROCRUSTES ROTATION OF WICKENS ET. AL. DATA



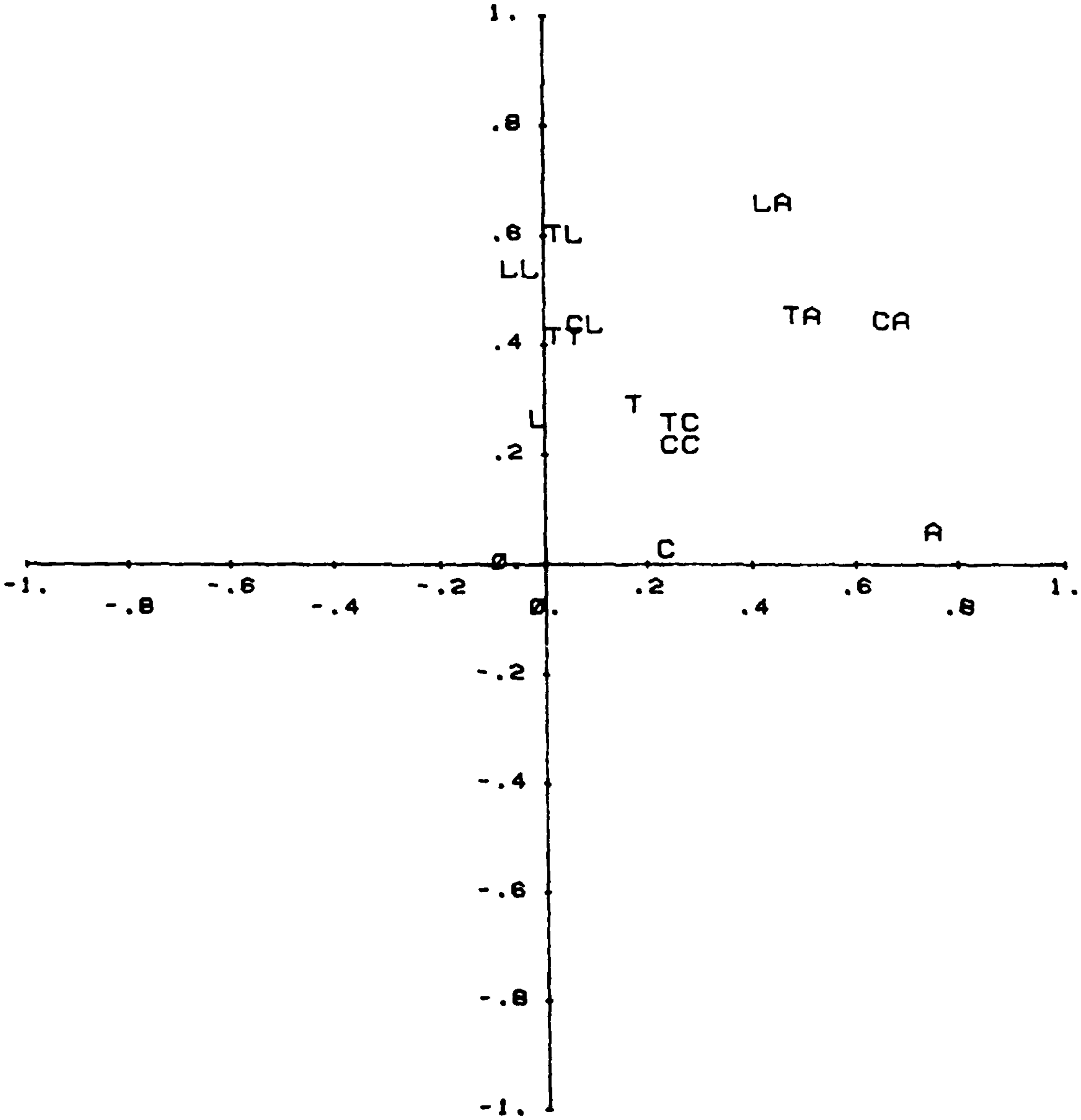
HORIZONTAL AXIS: FACTOR II -- CLASS. AND LINE.
VERTICAL AXIS   :   FACTOR III -- AUDITORY

FIGURE 2E: PROCRUSTES ROTATION OF WICKENS ET. AL. DATA



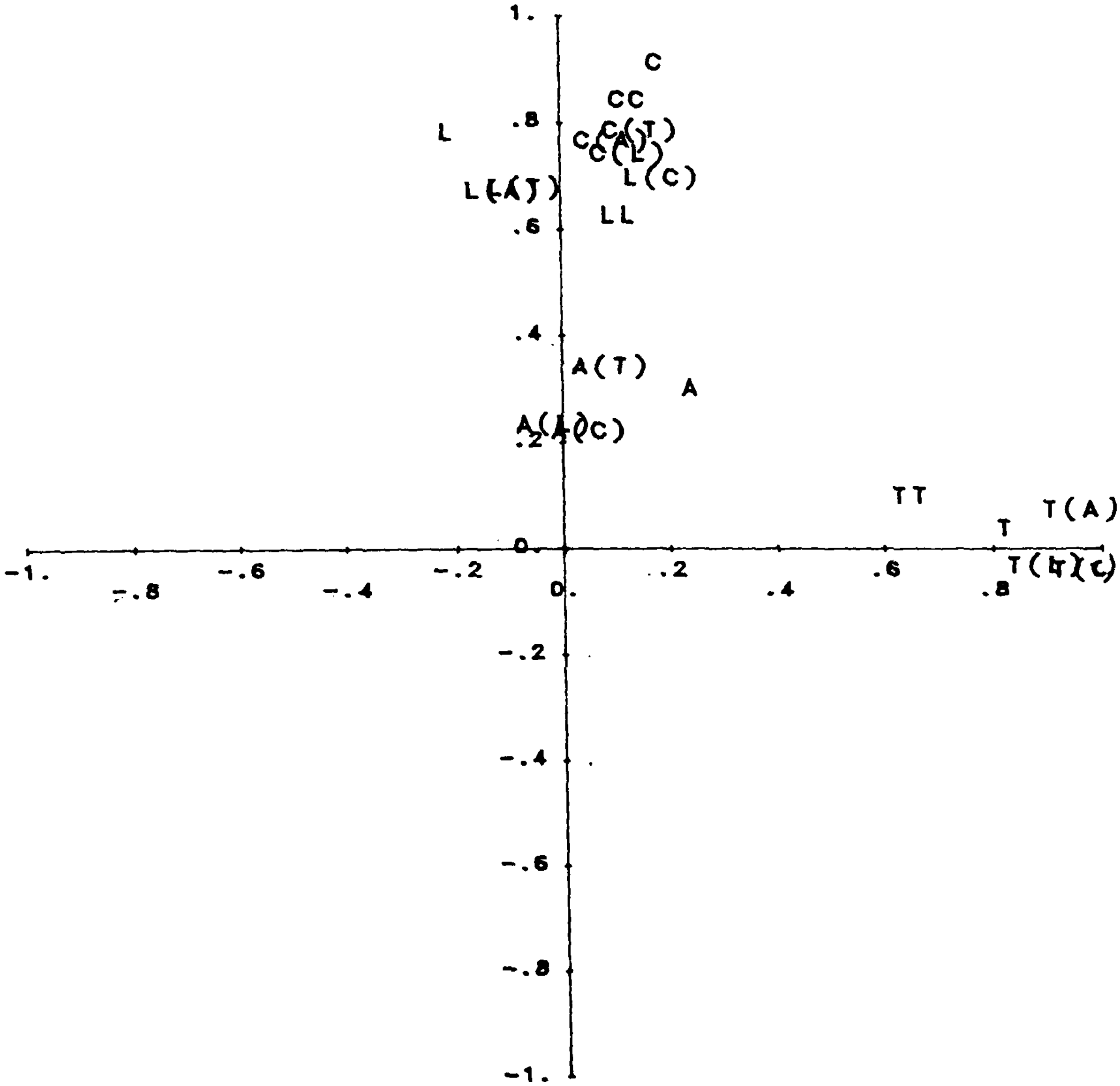
HORIZONTAL AXIS: FACTOR II -- CLASS. AND LINE.
VERTICAL AXIS : FACTOR IV -- TIME-SHARING

FIGURE 2F: PROCRUSTES ROTATION OF WICKENS ET. AL. DATA



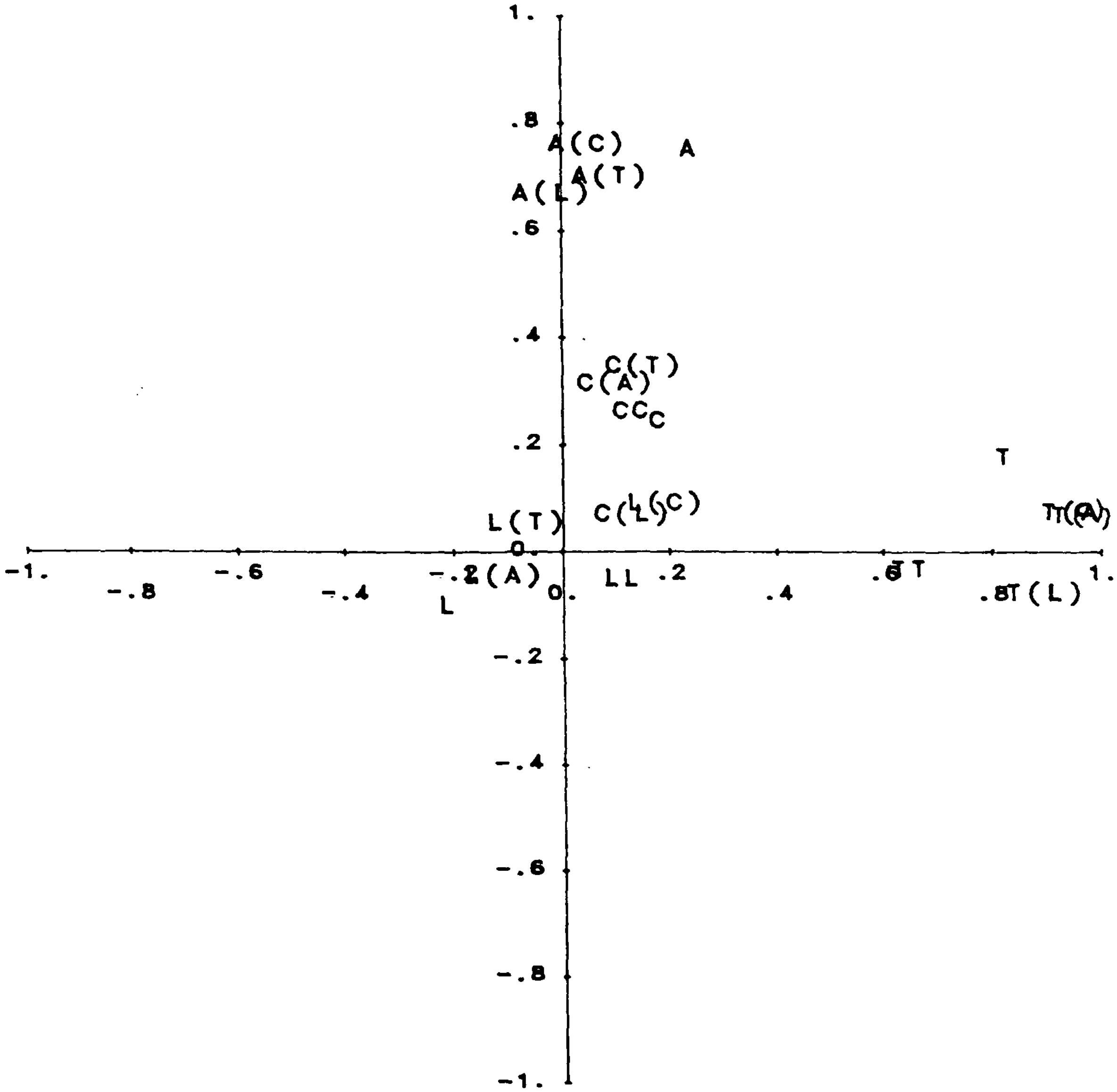
HORIZONTAL AXIS: FACTOR III -- AUDITORY
VERTICAL AXIS : FACTOR IV -- TIME-SHARING

FIGURE 3A: PROCRUSTES ROTATION OF WICKENS' RAW DATA



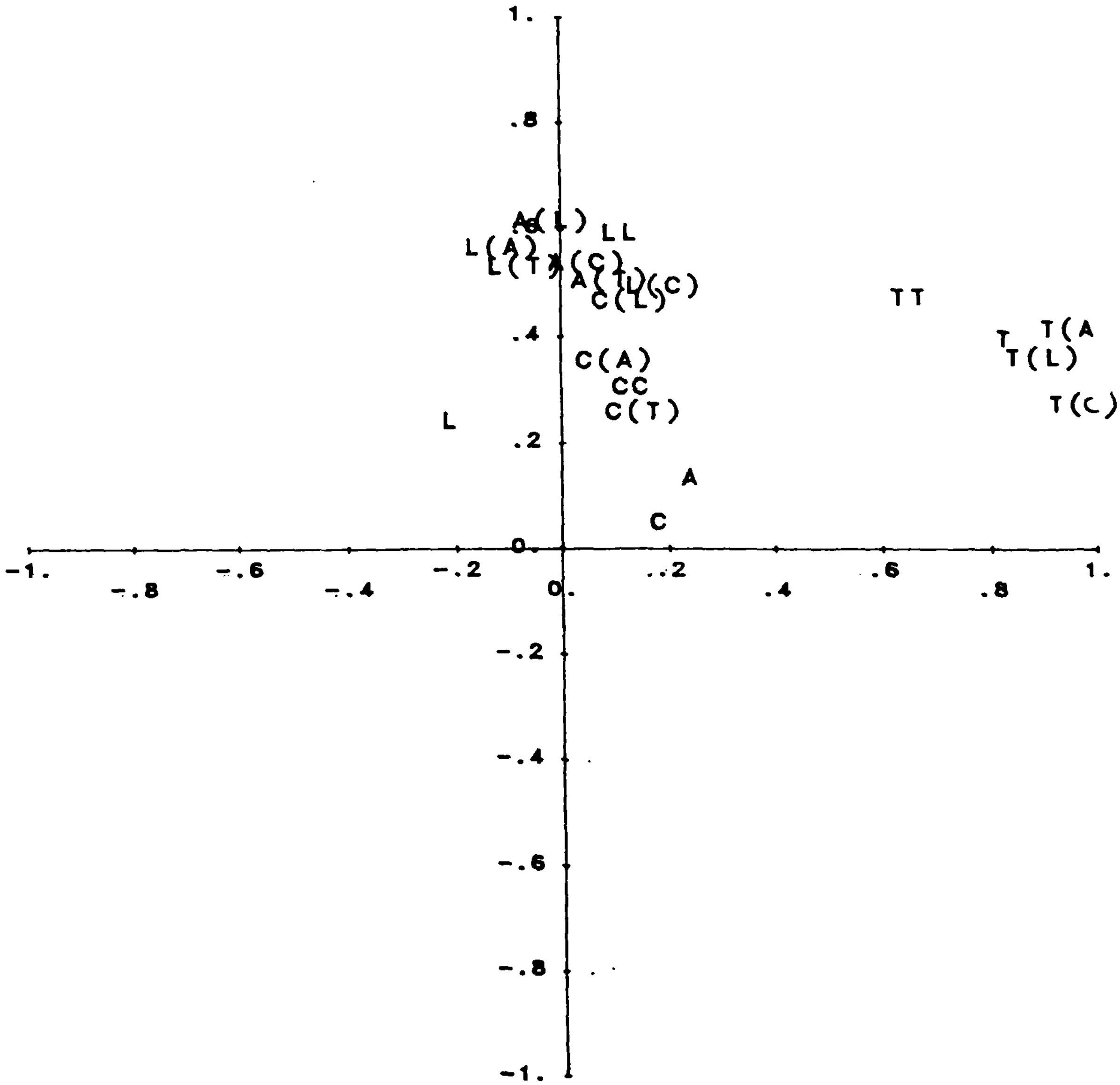
HORIZONTAL AXIS: FACTOR I -- TRACKING
VERTICAL AXIS : FACTOR II -- CLASS. AND LINE.

FIGURE 3B: PROCRUSTES ROTATION OF WICKENS' RAW DATA



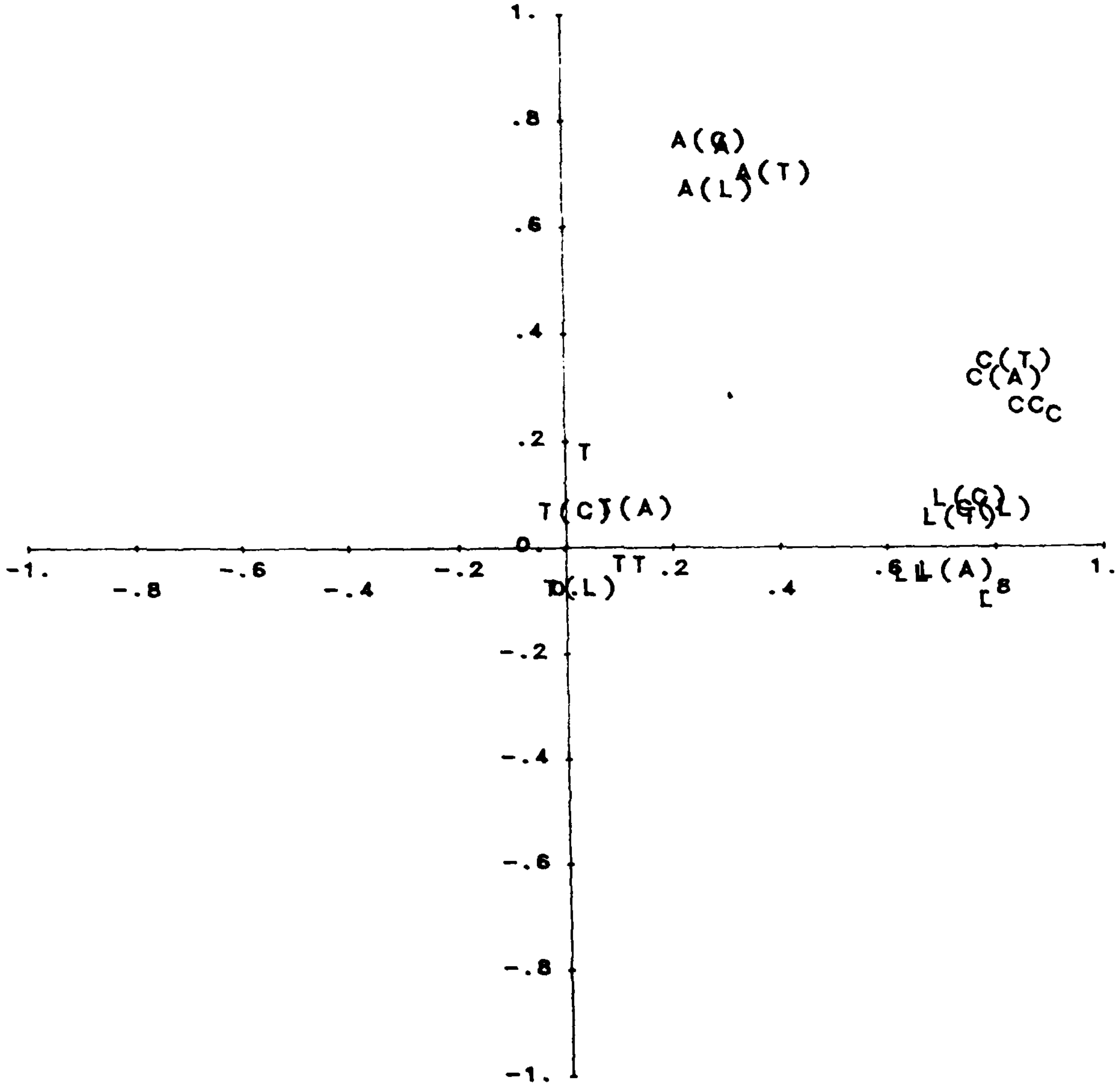
HORIZONTAL AXIS: FACTOR I -- TRACKING
VERTICAL AXIS : FACTOR III -- AUDITORY

FIGURE 3C: PROCRUSTES ROTATION OF WICKENS' RAW DATA



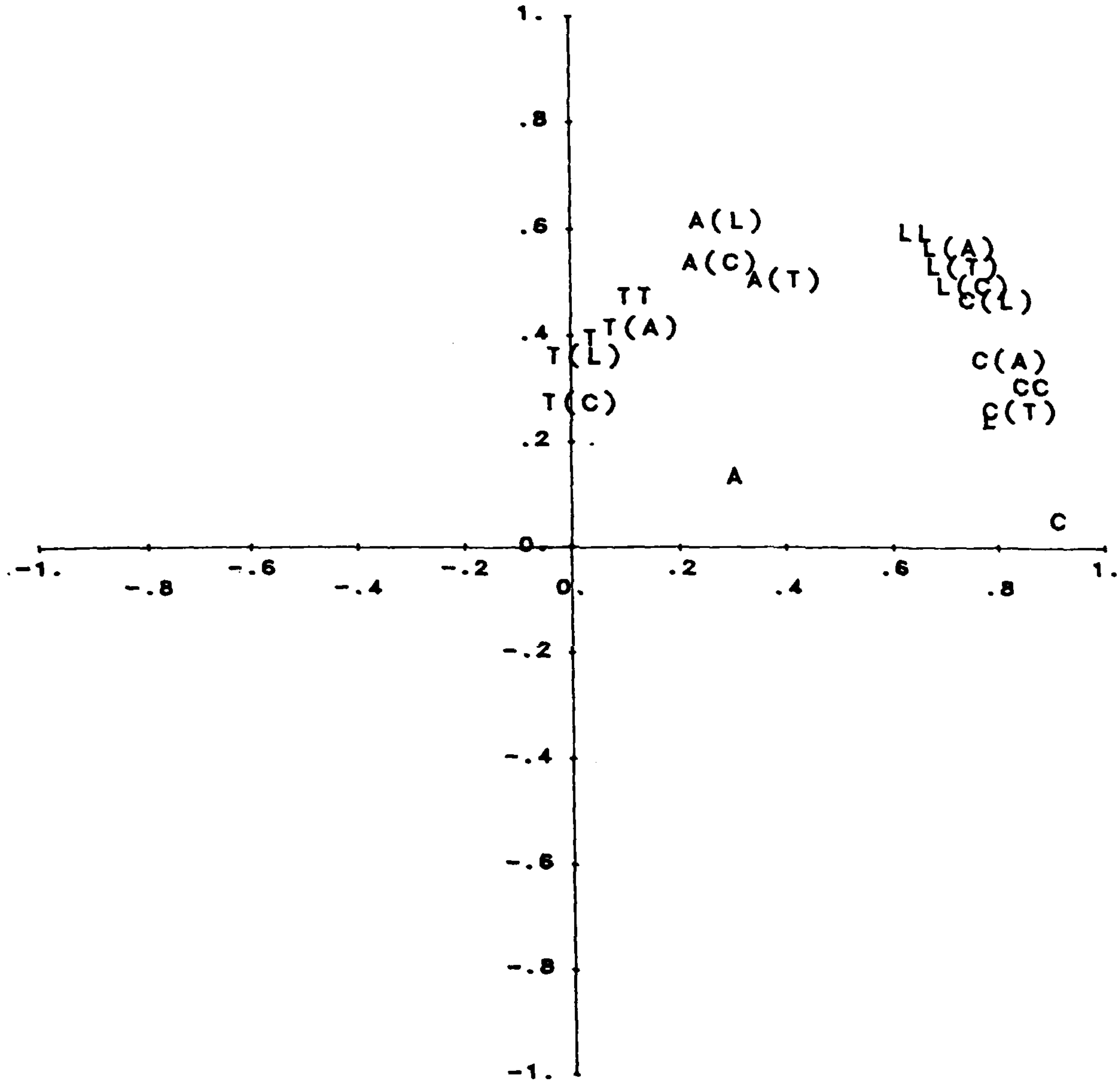
HORIZONTAL AXIS: FACTOR I -- TRACKING
VERTICAL AXIS : FACTOR IV -- TIME-SHARING

FIGURE 3D: PROCRUSTES ROTATION OF WICKENS' RAW DATA



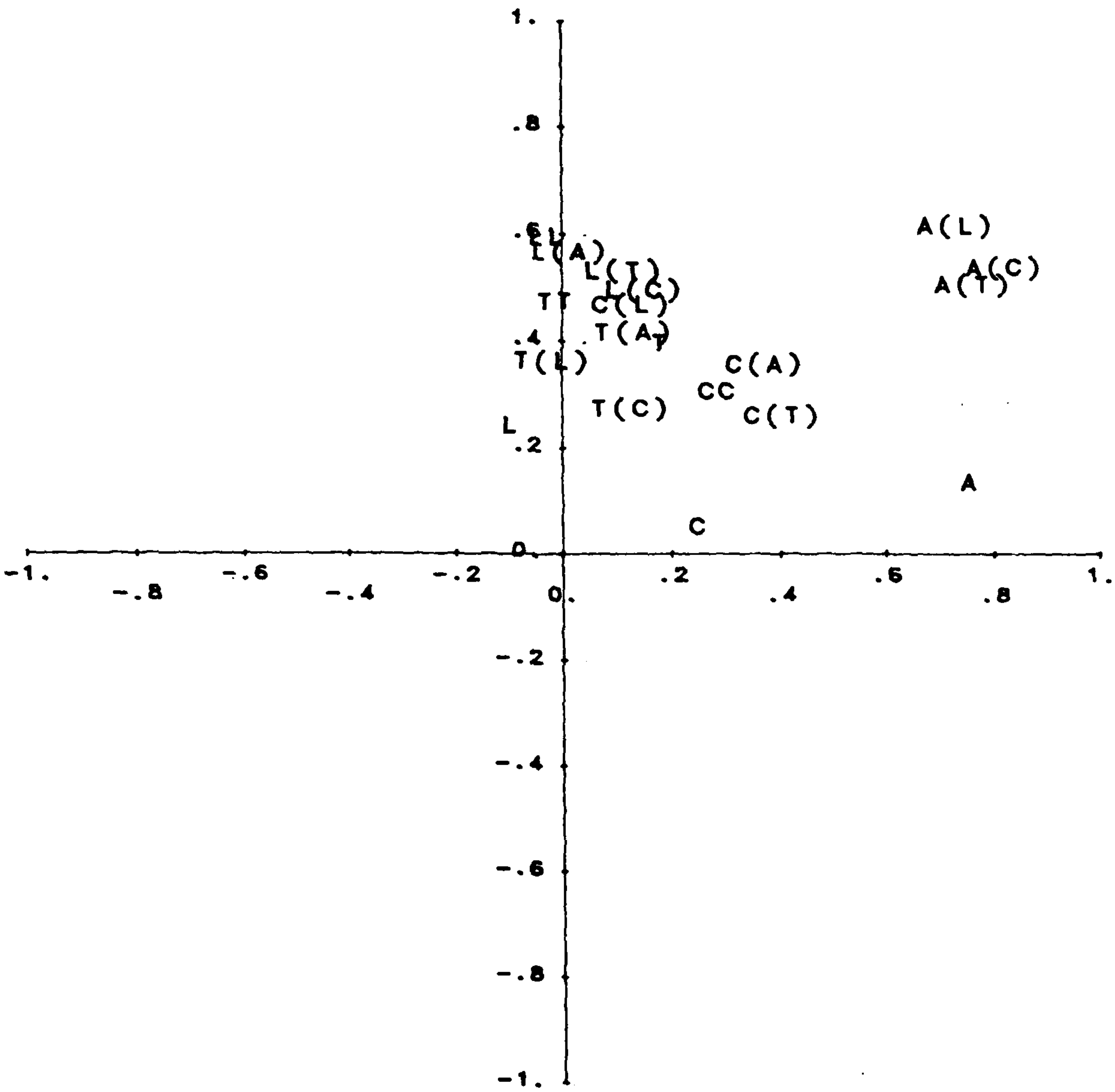
HORIZONTAL AXIS: FACTOR II -- CLASS. AND LINE.
VERTICAL AXIS : FACTOR III -- AUDITORY

FIGURE 3E: PROCRUSTES ROTATION OF WICKENS' RAW DATA



HORIZONTAL AXIS: FACTOR II -- CLASS. AND LINE.
VERTICAL AXIS : FACTOR.IV -- TIME-SHARING

FIGURE 3F: PROCRUSTES ROTATION OF WICKENS' RAW DATA



HORIZONTAL AXIS: FACTOR III -- AUDITORY
VERTICAL AXIS : FACTOR IV -- TIME-SHARING

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